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6 AN INVESTIGATION OF THE EFFECT OF PRODUCTION RATE VARIATION ON DIRECT LABOR REQUIREMENTS FOR MISSILE PRODUCTION PROGRAMS.

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The addition of the production rate variable to the standard learning curve model has been studied extensively, and has been validated as a significant technique in estimating direct labor hours for airframes, avionics equipment, and aircraft engines. This research set out to determine if the technique was applicable to air-launched missiles. The Maverick and Short Range Attack Missile (SRAM) production programs were evaluated yielding overall good results. Addition of the production rate variable contributed significantly to model estimating capabilities. It also significantly reduced auto-correlation of residuals in almost every case, thus enhancing the models' appropriateness for the data studied. The model could be useful in many missile production programs, but the specific program must be individually evaluated prior to model application. Model improvements were also implemented to reduce computer run-time, increase model flexibility, and provide residual analysis statistics.

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AN INVESTIGATION OF THE EFFECT OF PRODUCTION RATE VARIATION ON DIRECT LABOR REQUIREMENTS FOR MISSILE PRODUCTION PROGRAMS

A Thesis

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

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In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics Management

By

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has been accepted by the undersigned on behalf of the faculty of the School of Systems and Logistics in partial fulfillment of the requirements for the degree of

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Jack L. McChesney
COMMITTEE CHAIRMAN

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CHAPTER I

INTRODUCTION AND OVERVIEW

The last decade has introduced a bewildering era of complexity in Department of Defense (DOD) weapon system acquisitions. While primary concern has centered on the effective and efficient use of taxpayer dollars, numerous obstacles make this objective deceptively difficult to achieve. Tremendous leaps in technology have produced weapon systems of previously unimaginable complexity and cost. Further complicating the issue is the need to plan the acquisition and use of these weapon systems over as much as a 20-year time span with money that is appropriated by Congress one year at a time. Even more uncertainty has been added by shocks to the U.S. economy in the form of 1) inflation, 2) increasing cost and questionable availability of energy, and 3) increased competition from foreign countries.

The above-mentioned conditions have contributed to cost overruns in U.S. Air Force weapon system acquisitions, and clearly illustrate the need for more precise techniques to estimate the cost of these weapon systems. The experience of industry and the DOD indicates that direct labor is a significant determinant of cost. This research will focus on developing a better way to estimate direct labor costs and, more specifically, on the effect of a change in the rate of production on direct labor requirements.

Limiting the Problem

At the outset of a major DOD production program, a tentative monthly production schedule for the life of the program is negotiated between the contracting parties. This schedule permits planning for such items as work force buildup, facility and tooling needs, and the ordering of long lead-time items. Although the planning delivery schedule covers the life of the program, formal contractual agreements between the Department of Defense and manufacturers usually cover only annual delivery requirements. Delivery requirements for subsequent years are funded through the exercise of options or separate contracts as funds are appropriated by the Congress (15:2).

These multiple-year programs may result in a need to change the production rate. For example, when funding for a particular year is insufficient to cover the production scheduled under an existing production plan, it may be necessary to stretch out the production over a longer time span. A national emergency or changed mission requirement may dictate an accelerated rate of production. When such changes in delivery schedules are required, changes in cost estimates are also required to support contract negotiations and additional funding requests. It is suggested that the rate of production is an important independent variable that can be used to help project the change in costs due to either program accelerations or decelerations (15:2).

Industrial and government cost estimators have traditionally used learning curve techniques to estimate direct labor hours required in production (3:25). Learning curve theory is derived from the relationship between the cumulative number of units produced and the number of direct labor hours required for production. In other words, as a worker produces more of a given item, a certain amount of "learning" occurs, and the number of hours required for production tends to decrease in a regular pattern. This "learning" is not limited to improved manual dexterity of workmen. Other forms of learning include experience gained by managers that results in improved work methods, more efficient physical layout of the shop, more efficient parts supply, more efficient tools, etc. These forms of learning all result from experience gained from working with a system, and have led some authors to suggest that the learning curve should really be called the experience curve (14:63-64). Learning curve theory is based on the following assumptions:

1. The production item should be sizeable and complex and should require a large amount of direct labor.

2. The majority of assembly operations should not be mechanized or machine-paced.

3. Learning curves applied from past experience should be adjusted for any differences in items, process, or other aspects of production.

4. The production process should be a continuous one and the item and product changes kept to a minimum.

5. Historical data should be available to compute the curve since estimated data have low reliability.

6. There should be no external production rate changes (3:231).

The last assumption (no externally caused changes in production rate) is, as already indicated, unrealistic in the DOD arena. Changes in production rate are forced on DOD activities quite often. There has been considerable research conducted to correct this apparent limitation of the standard learning curve model. These studies will be discussed in Chapter II.

One of the most promising studies resulted in a model for airframe production developed by Larry L. Smith, which improved the basic learning curve model through the addition of a production rate variable. Smith's methodology has been replicated for aircraft avionics and engines to determine its validity in other types of production. Further replication in other weapon system applications is warranted, and forms the basis of this research effort.

Research Problem Statement

The effect of changes in the production rate on direct labor hours for continuing missile production programs is not known.

Research Objectives

The objective of this research is to apply Smith's model to determine: 1) if changes in production rate affect total direct labor hours per missile; 2) how the model compares with the basic learning curve model as a predictor of direct labor hours for continuing missile production; and 3) if Smith's approach for airframe production is applicable to missile production.

Research Hypotheses

The hypotheses to be tested in this research are: 1) that the production rate explains a significant amount of the variation in direct labor requirements for missile production, and 2) that the production rate model is a better predictor of direct labor requirements than the basic learning curve model.

Summary

With the problem narrowed and the objectives outlined, the next chapter is devoted to a review of past research approaches and findings. Chapter III will discuss the research hypotheses and the methodology for testing these hypotheses. A brief summary of assumptions and limitations about methodology will close Chapter III. Chapter IV will discuss data analysis and evaluation. Finally, Chapter V will contain the summary, conclusions, and recommendations of this research.

CHAPTER II

A HISTORY OF LEARNING CURVE THEORY AND ITS USE IN PREDICTING LABOR HOUR REQUIREMENTS

> The learning curve has been used extensively in the aircraft industry during the last thirty years to assist in cost estimating for major DOD weapons acquisition programs. Since the introduction of the basic learning curve model, a number of variations have been developed in an attempt to achieve a greater accuracy in predicting actual cost figures [6:6].

Since the standard learning curve model forms the basis for all variations that followed, this chapter will first discuss the original model and its limitations. Then a chronology of the major research efforts that resulted from the traditional model will follow.

Standard Learning Curve Model

T. P. Wright is generally regarded as the pioneer of learning curve theory. After his initial research, learning curve tables were in use at McCook Field, Dayton, Ohio as early as 1925 (4:49-50). Wright's 1936 article on the application of the learning curve to aircraft manufacturing cost estimation is widely regarded as the initial substantive effort in mathematically modeling the learning phenomenon for aircraft manufacturing (17:2D26). As a result of increased aircraft production during World War II, the U.S. Government sponsored a statistical analysis by the Stanford Research Institute on World War II airframe direct labor data. The Stanford study resulted in two important achievements: 1) it confirmed the learning curve effect on World War II production and 2) it demonstrated the value of a learning curve model for use in cost analysis (17:2D26-27).

It can be intuitively discerned that for labor production processes which are repetitious, each successive equivalent unit of production will require fewer direct manhours, and that the manhours required decrease at a decreasing rate. This phenomenon, known as the learning or experience curve, has two basic variations. The variation validated by the Stanford study is known as the "unit curve" or "Boeing" theory (11:2D28; 7:273), and can be expressed mathematically by the formula:

$$Y = AX^b$$

where:

- Y represents the direct labor hours for the "xth" unit,
- X represents the total number of units manufactured in the process,
- A represents the number of labor hours to produce the first unit manufactured in the process, and
- B represents the slope parameter or a function of the improvement rate.

The slope of the curve can be expressed as a percentage, which is the ratio between the per unit cost at any unit and the percent cost at double that number of units (2: 199). The "cumulative average" or "Northrop" variation (described by Wright in his 1936 article) measures the average cost for X units rather than cost for the xth unit. Its mathematical form is:

$$\bar{Y} = AX^B$$

"Where $\bar{Y}$ is the cumulative average cost of all production up to and including the xth unit. The other parameters are the same as for the unit curve theory [11:2D29]." While the Boeing and Northrop models can be manipulated in the same manner, the user should be aware of the difference between the unit cost and cumulative unit cost measured by these respective models. The unit learning curve will be the model used for the rest of this paper [6:7-9].

Limitations of the Standard Learning Curve Model

Probably due to its simplicity, intuitive appeal, and long history, the learning curve model is still widely used. However, the learning curve model does not take into account the exogenous changes in the rate of production. Those exogenous changes are a concern of this research, as is their effect upon the total direct labor requirements.

Concern about exogenous changes in production rate is justified by the following factors: (1) workers will adjust according to pressure to speed up or slow down production; (2) as more workers are employed, the distribution of tasks to each individual worker should narrow; and (3) at higher production rates, tooling costs can be more widely allocated to larger numbers of units (21:44).

Fiscal prudence dictates that each echelon within DOD strive for accurate cost prediction in order to budget, manage, and control. It naturally follows that the importance of production rates in cost estimating must be investigated fully, and that DOD buyers must consider the effects of production rate changes throughout the acquisition process [16:11].

History of Efforts to Add Production Rate Variable

The focus of this research involves the addition of the production rate as a second independent variable in the learning curve model. This section will present a chronological history of some of the more important work that has been done in this regard. The list is not exhaustive, and is intended only to provide the reader with a summary of the most widely recognized research efforts in this field. Not all researchers have agreed about the usefulness of the production rate variable. However, recent efforts show great promise for the production rate to aid in more accurate predictions of labor requirements.

Harold Asher Study

Asher examined the relationship between cost and quantity in the airframe industry. Using empirical data from several airframe production programs, he subjectively evaluated the effect of the production rate on direct labor hour requirements. Asher identified two ways in which the production rate could affect unit labor cost. First, it can affect the amount of machine set-up time charged to each unit of production. Second, it can affect the number of subassemblies in the manufacturing process which, in turn, affects the number of hours of subassembly work charged to each unit. He concluded that production rate was not very important as a predictor when compared to the effect of cumulative production (2:86-87).

Alchian and Allen Research

Alchian and Allen advanced the idea that production cost is dependent on three production variables: 1) total volume of the item to be produced, 2) production rate, and 3) amount of time from the decision to produce until the first output occurs (15:19). They drew three major conclusions. First, larger total volumes lead to smaller unit costs because of increased product standardization that accompanies larger volume. Second, unit costs increase with increasing production rates because more overtime and less efficient workers are needed to support the increased production rate. Third, the cost variable increases if the initial production start-up time is compressed. They explained that less efficient procedures are used than if time were allowed to prepare properly for production. Subsequent effort must be expended to correct these inefficiencies and results in higher unit costs (1:308-322).

Although Alchian and Allen did not test their conclusions on actual data, it is felt that their ideas may have application to the airframe industry (15:20).

Gordon J. Johnson Article

Johnson predicted labor requirements for rocket motors using an additive model which considered both the rate effect and the learning effect. The model he used was

$$y = A + BX_1 + CX_2^Z$$

where:

- y represents direct labor hours per month,
- X_1 represents production rate in equivalent units per month,
- X_2 represents cumulative units produced as of the end of each month, and
- A,B,C,Z are model parameters.

Johnson regressed this model against four sets of rocket motor data. His results are shown in Table 1. As depicted in the table, Johnson had good results (high R^2) with data sets 1 and 4, fair results with data set 2, and poor results with data set 3. Johnson explained data set 3's poor results as being due to an inadequate accounting system used by the manufacturer. He concluded that the production rate is a significant determinant of direct labor requirements [6:10].

TABLE 1

Summary of Johnson's Regression Analysis

Regression Variables	Coefficients of Determination (R^2)*			
	Data Set			
	1	2	3	4
Labor Hours vs Cumulative Units	.753	.395	.00678	.763
Labor Hours vs Cumulative Units & Production Rate	.932	.808	.308	.927

*R^2 represents the proportion of the variation in direct labor hours that is explained by the regression model.

Source: (8:34)

Joseph A. Orsini Thesis

Orsini (12:57-80) tested Johnson's rocket motor model using airframe data from the C-141 program. He employed the following procedure: 1) regression analysis was performed on the data using the standard unit learning curve model, 2) regression analysis was again performed using Johnson's three dimensional additive model that incorporated rate of production, and 3) analysis was performed after converting Johnson's additive model into a multiplicative one which is stated as follows:

$$Y = e^{\beta_0} \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

where

Y represents the direct labor hours per quarter,

X_1 represents the number of units produced per quarter,

X_2 represents the cumulative number of units produced as of the end of each quarter,

$\beta_0, \beta_1, \beta_2$ are model parameters, and

e is the base of natural logarithms.

Orsini concluded that 1) inclusion of the production rate as an independent variable significantly improved the predictive ability of both the additive and multiplicative models and 2) the multiplicative model performed better as a predictor than did the additive one because it eliminated the need to estimate the parameter Z (12:71).

Large, Hoffmayer, and Kontrovich Study

During an effort to develop a general cost model sponsored by the Office of the Secretary of Defense, these three investigators examined data from major airframe acquisitions relating to the effect of production rate on cost. The model used, according to Smith (15:29-30), is of the form:

$$Yi = A \cdot w^B \cdot s^C \cdot r^D$$

where:

Yi represents the cumulative direct manufacturing labor hours through unit number i,

w represents the program average weight in pounds as expressed by the Defense Contractor Planning Report (DCPR),

s represents the maximum design airspeed in knots,

r represents the production rate expressed as the acceptance span in months for the first i airframes (for their investigation Large, Hoffmayer, and Kontrovich chose i arbitrarily to be 100 or 200),

A,B,C,D are model parameters.

Large, Hoffmayer, and Kontrovich concluded that the effects of the production rate could not be predicted with confidence, especially in the early stages of a major acquisition. They felt that each case must be considered separately (9:50-51). Smith (15:31) indicated that the use of an acceptance span as a proxy for production rate masked the true effect of the production rate because of the resultant averaging effect.

Joseph Noah Research

Noah analyzed cost data to find the effect of production rate on airframe costs. His model for the data was:

$$y = e^{A} \cdot X_1^{B} \cdot X_2^{C} \cdot X_3^{D}$$

where:

- y represents average direct labor hours per pound of airframe for each airframe lot,
- e is the base of the natural logarithm,
- X_1 represents the cumulative volume in pounds of aircraft produced by the midpoint of each airframe lot,
- X_2 represents the production rate in average pounds of airframe delivered per month for the entire period,
- X_3 represents the annual volume of aircraft in airframe pounds, and
- A,B,C,D are model parameters.

Noah averaged the estimated regression coefficients from two sets of data, one on the F-4 and the other on the A-7, and tried to develop a generalized cost model. Smith felt that this approach was questionable and that the model needed to be tested on additional aircraft programs to determine if it did actually serve as an accurate predictor. Also, Smith stated that while the lot average airframe delivery rate was a practical representation of the production rate, the average delivery rate variable appears to lag the average expenditure of hours required to produce the airframes delivered [6:10, 12].

Larry L. Smith Dissertation

Smith developed a model for airframe production that included a production rate variable to test the idea that production rate changes can explain changes in direct labor requirements (15:35). He adapted a modified version of Orsini's multiplicative model as follows:

$$Y_i = \beta_0 \cdot X_{1i}^{\beta_1} \cdot X_{2i}^{\beta_2} \cdot 10^{e_i}$$

where:

Y_i represents the unit average direct labor hours needed to output each pound of airframe in lot i,

X_{1i} represents the cumulative learning accrued from experience on all airframes of the same type through lot i,

X_{2i} represents the production rate of lot i for all airframes of the same type,

e_i represents the variation of each dependent variable which is not explained by the two independent variables,

$\beta_0, \beta_1, \beta_2$ are parameters in the model (15:43).

Smith also linearized the model to facilitate multiple linear regression. The linearized form was (15:45):

$$\text{Log } Y_i = \text{Log } \beta_0 + \beta_1 \text{ Log } X_{1i} + \beta_2 \text{ Log } X_{2i} + ei$$

Smith used two proxies for the production rate variable. The "lot average manufacturing rate" included the number of airframes in a lot divided by the lot time span, where lot time span was the time between release date from the lot for the first airframe in the lot. The "lot delivery rate" was the actual monthly airframe acceptance rate (15:11-13).

To test the accuracy of his model versus the standard learning curve model, Smith employed a "reduced" model which was merely his model, or "full" model, minus the production rate variable. The "reduced" model was a unit learning curve model as follows (13:43):

$$Y_i = \beta_0 \cdot X_{1i}^{\beta 1} \cdot 10^{ei}$$

Regression of historical data with each model allowed Smith to identify the contribution of predictive ability by the production rate variable (16:17-18).

Evaluating data from the F-4, F-102, and KC-135 airframe production programs, Smith reached the following conclusions: 1) in each case, the production rate variable was negatively correlated with unit direct labor requirements, 2) both proxies to the production rate variable were important contributors to the full model's predictive ability, and 3) as evidenced by the R^2 values he obtained, the full model more closely fit the data than the reduced model (15:142-146). Tables 2 and 3 summarize Smith's regression analysis and predictive ability test results.

Congleton and Kinton Thesis

Using the same methodology, Congleton and Kinton replicated Smith's research for the T-38 and F-5 airframe production

TABLE 2

Summary of Smith's Regression Analysis**

Test Situation No.	Data Points	R_f^2 (actual)	R_r^2 (actual)	β_0	β_1	β_2
1	57	0.978	0.928	masked*	-0.261	-0.169
2	55	0.973	0.904	"	-0.246	-0.183
3	55	0.966	0.904	"	-0.257	-0.161
4	42	0.853	0.585	"	-0.230	-0.157
5	42	0.820	0.585	"	-0.229	-0.136
6	42	0.889	0.618	6.328	-0.221	-0.148
7	42	0.851	0.618	7.601	-0.219	-0.127
8	42	0.744	0.658	9.016	-0.279	-0.112
9	42	0.733	0.658	10.400	-0.278	-0.097
10	50	0.979	0.961	38.371	-0.299	-0.158
11	42	0.979	0.959	47.290	-0.344	-0.144
12	96	0.958	0.971	13.133	-0.453	-0.164
13***	7	0.974	0.903	0.674	-0.165	-0.305
14***	7	0.971	0.903	1.123	-0.233	-0.222
15***	7	0.994	0.964	13.338	-0.608	0.361
16***	7	0.992	0.964	7.303	-0.527	0.262

*The total production hours per pound were considered proprietary by the manufacturer, and these coefficients were masked in the published version of Smith's research (15:65).

**Smith's methodology, production rate proxies, and R^2 versus R^2 (actual) are all recapped in Chapters II and III of this research. The subscripts for R^2 are as follows: f stands for full model; r for the reduced.

***Impractical for test situations.

TABLE 3

Summary of Smith's Predictive Ability

Test Results

Test Situation No.	Percentage Deviation*	
	Full Model	Reduced Model
1	-2.6	14.5
2	2.2	13.6
3	Not Reported	13.6
4	1.8	5.3
5	3.1	5.3
6	-7.8	Not Reported
7	**	Not Reported
8	-0.7	1.1
9	-4.2	1.1
10	-1.1	5.6
11	3.5	Not Reported
12	2.2	-3.3
13-16	***	***

*These tests were conducted as described in Chapter IV of this research (15:56). All percentages are rounded to nearest tenth.

**Smith reported the results were deviations greater than than those for test situation 6, but did not report a value (15:96).

***Smith reported that predictive ability tests were impractical for situations 13 through 16 because observations were limited to seven (15:71-131).

programs. They reached the same basic conclusions as Smith; however, in one of the thirty test situations they reported that R^2 was higher for the reduced model than for the full model, but by less than one percent (5:91-93).

Stevens and Thomerson Thesis

Stevens and Thomerson replicated Smith's model for aircraft avionics systems. Specifically, they examined the Magnavox ARC-164 radio and the Teledyne Computer Signal Data Converter. After applying the methodology set forth by Smith, Stevens and Thomerson formed the following conclusions: 1) production rate was a significant explainer of variation in direct labor hours in nine of ten cases, 2) the predictive ability of the full model was better than that of the reduced model for 18 months into the future, 3) the standard learning curve (reduced) model consistently overestimated direct labor hours while the full model stabilized predictions over an extended interval, 4) regression coefficients are unique to the program for which they are derived, and 5) the overall applicability of Smith's model has wide potential and can be tailored to various other programs (16:102-104).

Crozier and McGann Thesis

Crozier and McGann also replicated Smith's research. They applied both the reduced model (standard learning curve) and the full model to three aircraft engine programs: 1) the General Electric J-79, 2) the Allison TF-41, and 3) the Pratt and Whitney F-100. They found that the production rate significantly explained variation in direct labor hours in three of six cases examined, with especially good results on the F-100 engine. On all engine programs, the full model was a better predictor than the reduced model. Crozier and McGann concluded that the results when using Smith's model depend a great deal on the type of weapon system. This last finding justifies the need for more replication efforts of Smith's model (6:92-94).

Summary

The dominant theme of the literature review has been the relationship between production rate and direct labor hour requirements. While not all researchers have agreed, there is significant evidence that production rate is an important contributor to the predictive ability of learning curves. This research will examine that relationship for selected missile production programs. Chapter III will outline the methodology used in this research effort.

CHAPTER III

RESEARCH METHODOLOGY

This chapter outlines the research hypotheses and the methodology used to test them. The chapter is divided into six sections as follows:

1) Objectives and Approach,
2) Model Variables,
3) Model Definitions and Assumptions,
4) Research Hypotheses,
5) Data Collection and Treatment,
6) Summary.

Objectives and Approach

The objectives of this research were: 1) to determine if the direct labor requirements for missile production were affected by the production rate, and 2) to determine if the production rate model was a better predictor of labor requirements than the basic learning curve model. Meeting these objectives also established the applicability of Smith's production rate model to missile production.

The approach was to collect historical production data from two missile programs, the Maverick manufactured by the Hughes Corporation, and the Short Range Attack Missile (SRAM) manufactured by the Boeing Company. These data were then evaluated using Smith's production rate model. As in all previous research using Smith's production rate model, the model was adjusted to specific data groups. No attempt was made to develop a generalized labor hour model to be used in all types of missile production.

Model Variables

The three variables evaluated in this analysis were:

1) direct labor hours,

2) cumulative output,

3) production rate.

Since it was desirable to improve the ability to predict direct labor hour requirements, this variable was designated as the dependent variable. Cumulative output and the production rate were treated as independent variables.

The Direct Labor Hours Variable

Direct labor is usually measured in hours, although it is occasionally measured in dollars. Whenever the data are expressed in dollars, care must be taken to accurately account for inflation. The primary determinants of total direct labor are: fabrication labor, assembly labor, and test labor. Depending on the individual contractor, the data may be expressed as total labor or any combination of the component parts (fabrication, assembly, and test). The exact form of the data is unimportant as long as a consistent unit of measurement is maintained.

The Cumulative Output Variable

Records are normally kept for the number of missiles completed each month. The cumulative output is the total number of missiles completed since the beginning of the production program as of the end of a specific accounting month.

The Production Rate Variable

The production rate is simply the number of missiles completed during an accounting month. For some production processes, the production rate is difficult to accurately assess. Whenever this situation occurs, a proxy must be developed for the production rate. Commonly used proxies are the delivery rate and the acceptance rate. A caution is in order whenever proxies are used. For example, the delivery rate (e.g. as reflected on DD Form 250 acceptance document) to an operational wing may bear little or no resemblance to the actual production rate at the plant. Actual production rates are preferrable if the data are available. If proxies must be used, they should be chosen with care so as not to entirely mask the effect of production rate variations.

Model Definitions and Assumptions

Chapter II discussed the two models used by Smith, which he called the "full model" and the "reduced model". For ease of reference, the models are repeated here.

Model Definitions

The reduced model is the basic learning curve where:

$$Y_i = \beta_0 \cdot X_{1i}^{\beta_1} \cdot 10^{e_i}$$

In the full model the production rate variable is added as follows:

$$Y_i = \beta_0 \cdot X_{1i}^{\beta_1} \cdot X_{2i}^{\beta_2} \cdot 10^{e_i}$$

The terms used in these models are defined as follows:

Y_i represents direct labor hours,

X_{1i} represents cumulative output,

X_{2i} represents the production rate,

e_i represents the variation which is left unexplained by the variables in the model, and

$\beta_0, \beta_1, \beta_2$ are regression coefficients.

To facilitate multiple linear regression of the two models, they were transformed to a linear form by taking the logarithm of each term. The logarithmic form of the reduced model is:

$$\text{Log } Y_i = \text{Log } \beta_0 + \beta_1 \text{ Log } X_{1i} + e_i$$

and the logarithmic form of the full model is:

$$\text{Log } Y_i = \text{Log } \beta_0 + \beta_1 \text{ Log } X_{1i} + \beta_2 \text{ Log } X_{2i} + e_i$$

Assumptions

The statistical significance of the results of the regression was tested using appropriate F-distribution statistics. To establish the validity of these tests, it was necessary to make some assumptions concerning the error terms in the model. First, the error terms were assumed to be normally distributed with a mean of zero and constant variance. Second, the error terms were assumed to be independent of each other and of the independent variables (10:30-31). The first two assumptions were tested using the procedures described in Criterion Test One (A).

A third assumption concerns a problem which frequently develops in multiple linear regression, that of multicollinearity. Multicollinearity exists when there is a high correlation between or among independent variables, which in this research were cumulative output and production rate. If a strong correlation exists between or among independent variables, the F-test may find the marginal contribution of one or more variables to be statistically insignificant when, in fact, they may be good explainers of variation in the dependent variable if considered separately (10:341).

While multicollinearity can be a serious problem if the model is to be used for control, it is not as serious a problem when the purpose of the model is to predict as was the case in this research (10:342). The contribution made by adding the production rate to the reduced model was subjectively evaluated by comparing predictions of the reduced model to those of the full model. Therefore, it was assumed the varying degrees of multicollinearity had no substantial impact on the short-range predictive abilities of the model.

Research Hypotheses

Two hypotheses were tested. The first hypothesis was that the production rate explained a significant amount of the variation in direct labor requirements for missile production. The second hypothesis was that the production rate (full) model predicted direct labor requirements for missile production better than the reduced model did.

Research Hypothesis One

The first research hypothesis was tested in two steps. The first step examined the statistical significance of the model's regression coefficients by regression analysis of historical missile production data. The second step involved the use of two criterion tests to evaluate the appropriateness of the model for the data. The dependent variable of the full model, in log-linear form, was subjected to regression analysis. The independent variables were the logarithms of cumulative output and the production rate.

Statistical Hypothesis One (A)

Statistical Hypothesis One (A) stated that the cumulative output variable and the production rate variable were related to labor hours as shown in the model. The null hypothesis and its alternative were formed as follows:

H_0: β_1 and $\beta_2 = 0$

H_1: $\beta_1 \neq 0$ and/or $\beta_2 \neq 0$

The decision rule was as follows: the null hypothesis was rejected if the test statistic (F-ratio) was greater than the critical statistic (F-critical) at the 0.05 level of significance. F-critical values were extracted from Neter and Wasserman's F-distribution tables (10:807-813).

Mathematically,

$$\text{F-ratio} = MSR/MSE$$

$$MSR = SSR/(p-1)$$

$$MSE = SSE/(n-p)$$

where:

MSR represents the mean of the regression sum of squares in logarithmic form,

MSE represents the mean of the error (or residual) sum of squares in logarithmic form,

SSR represents the regression sum of squares in logarithmic form,

SSE represents the error (or residual) sum of squares in logarithmic form,

n represents the number of observations, and

p represents the number of parameters in the model (10:45, 79, 227-228).

The F-ratio compared the explained variance (MSR) to the unexplained variance (MSE), and thus determined the ability of the model to explain the variance of the dependent variable.

Statistical Hypothesis One (B)

The hypothesis tested the ability of the production rate variable, when combined with the cumulative output variable, to explain additional variation in direct labor hours per missile. Statistically, the null and alternate hypotheses were:

H_0: $\beta_2 = 0$

H_1: $\beta_2 \neq 0$

As before, the null hypothesis was rejected if the test statistic F* was greater than the critical statistic F_c at the 0.05 level of significance. The value of F* was determined as follows:

$$F^* = \frac{\Delta R^2/g}{(1-R^2)/(n-k-1)}$$

where:

ΔR^2 represents the increase in explained variation caused by the addition of the logarithm of the production rate variable to the reduced model,

R^2 represents the amount of variation in direct labor hours explained by the logarithmic form of the full model,

g represents the number of variables (in this case, one) which cause the increase in R^2,

n represents the number of observations,

k represents the total number of regressors, and

n-k-1 represents the degrees of freedom in the unexplained variation (18:435).

The F* statistic in this test yielded a ratio of the increase in explained variance to the remaining unexplained variance which resulted from introducing the production rate variable into the reduced model.

However, Neter and Wasserman (10:253) indicate that the increase in explained variance caused by introducing the production rate variable must be qualified if correlation (multicollinearity) exists between the independent variables. Whenever correlation exists, the increase in explained variance is not solely the result of adding the new independent variable. So, when the production rate variable is added to the model, the magnitude of the change in explained variance is partially caused by the already present effect of the cumulative output variable.

> When independent variables are correlated, there is no unique sum of squares which can be ascribed to an independent variable as reflecting its effect in reducing the total variation in Y. The reduction in the total variation ascribed to an independent variable must be viewed in the context of other independent variables included in the model whenever the independent variables are correlated [10:253].

Criterion Test One (A)

The first criterion test for the appropriateness of the model concerned the assumptions about the residuals, or observed errors. The model was considered appropriate for the data if assumptions about constant variance of residuals, independence of residuals, and normal distribution of residuals could not be rejected on the basis of appropriate tests (10:240).

The assumption of constant variance of residuals was tested by plotting the residual values against the predicted values of the dependent variable. The assumption was accepted if the plot revealed an even distribution (no discernible pattern) and if most residuals were within one standard error of the estimate (10:239-240).

The Durbin-Watson Test (11:358-361, 816) was used to check for independence of residuals. The test determined whether or not the autocorrelation parameter ρ was equal to zero. The test alternatives were:

H_0: $\rho > 0$

H_1: $\rho = 0$

A statistical package called "STAT II" in the Copper Impact Library at the Air Force Institute of Technology calculated the Durbin-Watson statistic designated as D. Table A-6 in the Neter and Wasserman text contained upper and lower bounds (d_u and d_L) for various sample sizes, levels of significance, and numbers of independent variables. The calculated statistic D was compared to the upper and lower bounds in the table at the .05 level of significance. The decision rule was as follows:

If $D < d_u$, conclude H_0

If $D > d_L$, conclude H_1

If $d_L \leq D \leq d_u$, the test is inconclusive.

If alternative H_1 was concluded, the residuals were considered to be independent.

The assumption of normal distribution of residuals was tested in two ways. The first, and more stringent, test was the Kolmogorov-Smirnov (K-S) test. If the K-S test indicated a problem, then the residuals were plotted on normal probability paper to see if the plot approximated a straight line (11:107-108, 112).

The basis of the K-S estimation procedure is the cumulative sample function, which is denoted by S(X). S(X) specifies for each value of X the proportion of values less than or equal to X, i.e. S(X) is simply a step-function ogive (11:403). The K-S procedure utilizes a statistic, denoted by D(n), which is based on the differences between the cumulative sample function S(X) and the true cumulative probability function F(X).

$$D(n) = \text{Max}|S(X) - F(X)|$$

In other words, D(n) equals the largest absolute deviation of S(X) from F(X) at any value of X. D(n) is shown as a function of n because it depends on the sample size. Surprisingly, however, it does not depend on the specific form of F(X). Hence the K-S procedure may be used for goodness of fit tests for any shape distribution, and was used in this case to see if the residuals were normally distributed (11:403-404).

The K-S statistic used in this research was calculated by the STAT II package in the Copper Impact Library. If the calculated statistic was below the critical value in the D(n) table (10:709), the data were considered normal. Stated in hypothesis form:

H_0: K-S* $\geq D(n)_c$

H_1: K-S* $< D(n)_c$

Criterion Test One (B)

The second test of the appropriateness of the model involved the use of the multiple coefficient of determination, known as R^2. The R^2 value measured the proportion of variation in direct labor hours that was explained by the regression model. R^2 was calculated by subtracting the quotient of SSE/SSTO from one. The error sum of squares, SSE, was the summation of all squared residuals, and was formally defined in statistical hypothesis one (A). The total sum of squares, SSTO, was calculated by summing the squared differences between each observed value and the mean of the dependent variable (10:77).

In this model, R^2 as a valid measure of explained variation was somewhat obscured by the transformation of the model to the logarithmic form. R^2 in that form represented the logarithmic value of direct labor hour variation rather than variation in actual hours. Smith, in his research, developed a more meaningful statistic which he called R^2 (actual) (15:53). R^2 (actual) was calculated in the same way that R^2 was, except that the SSE and SSTO values were calculated after transforming the observed and predicted values of the dependent variable from logarithmic to actual form. In that way, the variation was represented in actual hours instead of logarithms.

An appropriate model for the data would explain a high proportion of variation in direct labor, and would consequently yield a high R^2 (actual). Therefore, in this criterion test, an R^2 (actual) value of .75 or higher was selected as the level at which the model could not be rejected as inappropriate.

If the model was not rejected by either of the statistical tests or criterion tests, its predictive ability was then tested under research hypothesis two.

Research Hypothesis Two

As stressed in Chapter I, a primary objective of this research was to determine which form of the learning curve would best predict direct labor hour requirements in a continuing missile production program. After the full model was successfully developed under research hypothesis one, its predictive ability was compared to that of the reduced model. Research Hypothesis Two stated that the full model would be a better predictor than the reduced model.

Smith's production rate model simulated future predictive ability by performing a stepwise truncation of the historical data. Smith described the process as follows:

> In a real application of the model, the prediction would be beyond the range of the historical data. The only way to test the accuracy of the prediction would be to wait and see how many hours it takes to build the next airframe lot. To simulate this situation, the regression coefficients in the model are estimated with the last few observed data points omitted. Then using the new model, omitted values (which are known but not used in estimating the model coefficients) are predicted. Comparisons are then drawn between the actual and predicted hours as a subjective measure of predictive ability [15:56].

In this research, 12 data points were omitted and then predicted. Twelve data points were chosen to simulate the typical "real world" application of learning curve models to estimate costs for the next fiscal year (12 months) of production.

The second research hypothesis was evaluated using both a statistical hypothesis and a criterion test. The statistical hypothesis was used to determine whether the full model was significantly better than the reduced model in predicting the labor hour values omitted in the prediction simulation. Where the full model was found to be a significantly better predictor based on the statistical test, a criterion test was then applied to established whether the improved predictive ability of the full model had a practical significance as well.

<u>Statistical Hypothesis Two</u>

A statistical test was performed to determine if the average absolute deviation of the full model ($|\bar{D}_F|$) was significantly less than that of the reduced model ($|\bar{D}_R|$). The average absolute deviation for each model was computed by taking the absolute value of the difference between the actual and predicted direct labor hours occurring in each test situation, then separately summing the absolute deviations for each model in all test situations. Statistically, the null and alternate hypotheses were:

$$H_0: \quad |\bar{D}_R| \leq |\bar{D}_F|$$

$$H_1: \quad |D_R| > |D_F|$$

The hypothesis was tested using the Student's t distribution (less than 60 test situations) and the Z statistic (more than 60 test situations). The assumptions of normal distribution and randomness of the deviations, examined in research hypothesis one, remained in effect during this test. The decision rule using the Student's t statistic was as follows:

Reject H_0 if $t > t_c(.05)$

where:

$$t = (|\bar{D}_R| - |\bar{D}_F|)/\sqrt{(S_R^2/N) + (S_F^2/N)}$$

and

S_R^2 represents the variance of the distribution of deviations obtained with the reduced model,

S_F^2 represents the variance of the distribution of deviations obtained with the full model,

N represents the number of test situations,

t_c represents the critical t value obtained from a table of Student's t critical values (18:208-215).

Criterion Test Two

Where the improved predictive ability of the full model over the reduced model was shown to be statistically significant, the model was then subjected to a test of practical significance. This test was necessary because 1) the reduced model, although shown to be a statistically less accurate predictor, could still be sufficiently accurate for practical application, or 2) the full model, although shown to be a statistically better predictor than the reduced model, could still be so inaccurate as to be of no value in practical application. In either instance, the addition of the production rate variable would not be considered worthwhile from a cost/benefit standpoint.

To perform the criterion test, the individual deviations computed for the full and reduced models in each test situation under statistical hypothesis two were converted into a measure of deviation expressed as a percentage of the actual direct labor hours. The use of percentages facilitated comparison of results between programs whose values for direct labor hours were relatively small and programs whose values for direct labor hours were relatively large. Two categories were then established for the deviations.

These categories provided a basis for comparison of the predictive ability of the two models. When percentage deviations fell in the range from greater than five percent to ten percent, the predictive ability was categorized as good. When percentage deviations were five percent or less, the predictive ability was categorized as excellent. The number of test situations in which the percentage deviations fell into each category was then separately summed for the full and reduced models. Totals for each category and model were then subjectively compared and the model with the greater total number of good and excellent predictions was judged to have the better practical predictive ability.

Data Collection and Treatment

Historical data from two separate missile production programs, SRAM and Maverick, were collected. Because of differences in programs, data collection and treatment of the model variables are discussed separately for each program. Pertinent background information and treatment of the variables will be discussed first for SRAM and then for Maverick.

The SRAM Program

The AGM-69, better known as SRAM, was produced by the Boeing Aerospace Company in three production runs (A, B, and C) for use on the B-52, FB-111, and was projected for use on the B-1. Production of this air-launched missile occurred from February of 1972 through August of 1975, a period of 42 months.

There were three elements of production direct labor hours for the SRAM program:[1] fabrication, minor assembly, and major assembly. Fabrication was defined as shop effort expended in the manufacture of individual detail parts in economic lot sizes. This effort included such activities as shearing, shaping, drilling, and machining. Minor assembly was defined as shop effort expended in joining of detail parts by methods such as welding, riveting, soldering, and bolting. Minor assembly was normally conducted in economic lot sizes. Major assembly was defined as shop effort expended in joining sub-assemblies into a final product and included a functional test of the end product. Major assembly was conducted on a unit by unit basis.

At the one hundredth unit of production, an accounting change caused an aberration in the labor hours for fabrication and minor assembly. Adding the fabrication hours and minor assembly hours resolved this problem. Therefore, for the

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[1]This information was obtained during a visit to the manufacturer's plant in Seattle, Washington in December 1979.

purpose of this research, fabrication and minor assembly were considered together as one category.

The SRAM data were collected from two sources. The Boeing Company provided data for the dependent variable, actual direct labor hours per missile. The Boeing data also contained delivery rates to operational wings as recorded on DD Forms 250. As indicated before, delivery rate can be used as a proxy for the production rate. The Strategic Systems Program Office (Strategic SPO) at Wright-Patterson AFB provided data for the independent variables, cumulative output and production rate. This data contained the actual production rate per accounting month. Accounting months were derived using a perpetual calendar to identify the number of working days per calendar month. A problem was encountered with this data in that some of the information was missing. Of the 42 possible data points, only 22 were available, thereby creating an unintended sample of the overall population. The possibility of sampling error decreased the confidence in the analysis results. However, the sample was large enough to generalize the results to the population. An exact sampling error could not be computed because the sample was not randomly chosen.

Four models were derived from the SRAM data based on various treatments of the variables. The four models and treatment of the variables within each model are discussed below.

Model 1. The dependent variable for Model 1 was designated Y_f and represented the fabrication/minor assembly component of total direct labor hours. The independent variables were treated the same for Models 1 through 3 and are discussed here, but not repeated in the discussion of Models 2 and 3. The production rate used was designated X_2 and was the actual production rate obtained from the Strategic SPO. Summing each month's actual production rate resulted in the cumulative output variable which was designated X_1.

Model 2. The dependent variable for Model 2 was designated as Y_a and represented the major assembly portion of total direct labor hours per unit.

Model 3. The dependent variable for Model 3 was designated Y_t and represented the sum of total direct labor hours per unit.

Model 4. The dependent variable for Model 4 was designated Y_t and represented total direct labor hours per unit. However, differing from Models 1 through 3, the delivery rate (DD250) was used as a proxy for the actual production rate. Model 4 was used for two reasons: 1) to assess the performance of the delivery rate as a proxy for the actual production rate, and 2) the use of the delivery rate proxy allowed the utilization of all 42 data points (months) and provided a point of reference to ascertain the severity of the sampling error in Models 1 through 3. The delivery rate data were recorded by calendar month. Once again, summing each month's delivery rate resulted in the cumulative output.

The Maverick Program

Production of the air-launched Maverick missile (AGM-65) occurred from April 1972 through April 1978, resulting in 73 data points (months). Data for the Maverick program were obtained through the cooperation of personnel at the Hughes Aircraft Company plant in Tuscon, Arizona. The elements of direct labor hours (fabrication, assembly, and test) were essentially the same as for SRAM, with two notable exceptions. First, the hours for testing of end-items were recorded separately rather than being included as part of assembly. Second, all labor hours whether they be fabrication, assembly or test were separated into two component parts. These two components were called Standard Hours and the Unit Index.

Standard Hours represented the number of hours required to perform a specified task under ideal conditions as determined by time and motion studies. Standard Hours corresponded to learning that resulted from methods improvements during the life of the program. The Unit Index measured the deviation between actual performance and the ideal standard. The Unit Index corresponded to "hands on" labor learning that occurred during the program. When multiplied together, Standard Hours and the Unit Index resulted in actual direct labor hours used to accomplish a major task (such as fabrication, assembly, or test).

The dependent variable, then, was calculated by multiplying standard hours by the unit index to obtain direct labor hours. The raw data did not specify the actual number of hours on a unit by unit basis, but averaged the total number of hours expended on all units produced during an accounting month. This system resulted in Maverick labor hours being reported on an equivalent unit basis. Derivation of the independent variables was done in the same manner as for the SRAM program. The actual monthly production rate reported by Hughes was available for all 73 months of production. The production rate was simply the number of missiles completed during an accounting month and was designated as X_2. Summing each month's production rate yielded the cumulative output, designated as X_1.

Eight models were developed for the Maverick program and were designated as Models 5 through 12. The models are discussed below.

Model 5. The dependent variable for Model 5 was designated as Y_f and represented the fabrication portion of average total direct labor hours per equivalent unit. The independent variables were developed as indicated above for all eight models and are not discussed here.

Model 6. The dependent variable for Model 6 was designated Y_a and represented assembly labor hours per equivalent unit.

Model 7. The dependent variable for Model 7 was designated Y_{tst} and represented test labor hours per equivalent unit.

Model 8. The dependent variable for Model 8 was designated Y_t and represented the sum of total direct labor hours per equivalent unit.

Model 9. The dependent variable for Model 9 was designated Y_{tu} and represented the unit index portion of total direct labor hours per equivalent unit.

Model 10. The dependent variable for Model 10 was designated Y_{tsh} and represented the standard hours posi-tion of total direct labor hours per equivalent unit.

Model 11. The dependent variable for Model 11 was designated Y_{fu} and represented the unit index portion of fabrication hours per equivalent unit.

Model 12. The dependent variable for Model 12 was designated Y_{fsh} and represented the standard hours position of fabrication hours per equivalent unit.

Models 9 through 12 were included to be able to assess the relative effects of standard hours (methods improvements) and the unit index (labor learning by the workmen). Total hours and fabrication hours were the only models evaluated in this manner because of limited computer resources.

Data Treatment Summary

Historical production data were gathered for the SRAM program and the Maverick program. The data were used to develop one dependent and two independent variables for use in multiple linear regression analysis. Various combinations of the data resulted in 12 models which are summarized in Table 4.

Summary

Historical production data were analyzed using least squares multiple linear regression. The research hypotheses

TABLE 4

Summary of Models for Regression

Model	Program	Dependent Variable (direct labor hours)
1	SRAM	fabrication/minor assembly hours
2	SRAM	major assembly hours
3	SRAM	total hours
4	SRAM	total hours*
5	Maverick	fabrication hours
6	Maverick	assembly hours
7	Maverick	test hours
8	Maverick	total hours
9	Maverick	total hours** (unit index)
10	Maverick	total hours** (standard hours)
11	Maverick	fabrication hours** (unit index)
12	Maverick	fabrication hours** (standard hours)

*For Model 4, the delivery rate as recorded on DD Form 250 was used as a proxy for the actual production rate.
**Models 9 through 12 were included to show the comparative effect of the unit index (labor learning by the workmen) versus standard hours (methods improvements).

were tested using the statistical and criterion tests described in this chapter.

The first hypothesis was evaluated using two statistical tests and two criterion tests. If all tests were passed, the full model was validated. The conclusion sought was that the production rate explained a significant amount of the variation in direct labor hour requirements for missile production.

The second research hypothesis was evaluated using one statistical test and one criterion test. If both tests were passed, the full model was shown to have better practical predictive ability than the reduced model.

Certain assumptions were necessary for the regression model to be appropriate. The strength and validity of the conclusions drawn from the research hypotheses were dependent on the applicability of these assumptions. Further, the methodology contained certain limitations which must be considered. A summary of the assumptions and limitations follows.

Assumptions

1. Historical data obtained from the manufacturer and the program office were recorded accurately.

2. Multicollinearity did not impair the short-range predictive ability of the models.

3. Data measurements and transformations were accurate.

4. No significant loss of data precision was induced by the logarithmic transformation of the data used to facilitate multiple linear regression.

5. The error terms had a normal distribution with a mean of zero, constant variance, and were statistically independent.

Limitations

1. Subjective analysis was required to assess the

validity of the assumption concerning constant variance of error terms.

2. Information derived from the data for a specific program can be applied only to that program.

Having employed the methodology just described, Chapter IV presents the results of the data analysis and evaluation.

CHAPTER IV

DATA ANALYSIS AND EVALUATION

This chapter presents analysis of production data for the two missile programs utilizing the methodology described in Chapter III. It is divided into three sections, beginning with analysis of the SRAM data in Models 1 through 4. The next section discusses analysis of the Maverick data with Models 5 through 12. Each of these sections describes the production program, the data, results of hypothesis testing, and major findings. The last section summarizes the findings for both production programs, compares and contrasts them, and evaluates the overall applicability of the full model to the two programs.

The SRAM Program

As stated in Chapter III, the data for SRAM program analysis were obtained from two sources. The Boeing Company provided the data for the dependent variable, direct labor hours per missile. The Strategic Systems Program Office provided the data for the independent variables, cumulative production and production rate. Fifteen hundred missiles were manufactured with no breaks in production from February 1972 to August 1975, a total of 42 months. As described in Chapter III, there were time gaps in the production rate data that allowed use of only 22 of the 42 possible data points. Because this sample was used instead of a census, confidence in the analysis results was decreased somewhat due to the possibility of sampling error. However, the sample size was large enough to generalize the analysis results to the population.

Aside from the potential sampling error problem described above, the SRAM program provided a good test situation for the research. The total direct labor data were broken down into two major components, fabrication/minor assembly and major assembly. This partitioning of the total labor hours permitted the researchers to assess the differing effects of the production rate on the two different aspects of labor. Additionally, the cumulative output and production rate data reflected actual results experienced on the production line. As a consequence, development of a less accurate production rate proxy was not required. Finally, the SRAM production history did not reveal any major design, production, or accounting changes.

The raw data were transformed as described in the explanation of the individual variables for each of the models presented in Chapter III. Regression analysis was performed on both the reduced and full forms of the models, and test statistics were calculated.[2] The test statistics were then

[2]The primary regression results used throughout this research were obtained through use of Smith's FORTRAN IV program which was extensively modified by the authors. This

compared with the critical values required, and the criterion tests were applied to determine if the first research hypothesis was supported. If the results for a particular model supported research hypothesis one and the criterion tests failed to reject the model as inappropriate, that model was then tested for support of research hypothesis two. Even if the model was rejected as inappropriate under research hypothesis one, tests for research hypothesis two were presented for subjective evaluation, recognizing that statistical inferences could not be made with confidence.

Analysis of Research Hypothesis One

The statistical hypotheses and criterion tests for research hypothesis one are restated below in summary form for ease of reference.

Research Hypothesis One. The production rate explains a significant portion of the variation in total direct labor requirements for missile production when included in an appropriate model.

Statistical Hypothesis One (A). H_0: β_1 and $\beta_2 = 0$; H_1: $\beta_1 \neq 0$ and/or $\beta_2 \neq 0$. Reject H_0 if F Ratio is greater than F_c.

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modified program is listed and described in the Appendix. A similar program is available for use by government price analysts through the COPPER IMPACT Library under the file name PRODRATE.

Statistical Hypothesis One (B). H_0: $\beta_2 = 0$; H_1: $\beta_2 \neq 0$; reject H_0 if F* is greater than F_c.

Criterion Test One (A). The model's appropriateness cannot be rejected if an analysis of the residuals indicates the assumptions of constant variance, independence, and normality are not violated.

Criterion Test One (B). The model's appropriateness cannot be rejected if the computed R^2 (actual) is greater than 75 percent.

Test results for research hypothesis one are presented in tabular format for each model tested. Recall that Models 1, 2, and 3 have the same values for the independent variables (plant actuals) but different dependent variables; fabrication/minor assembly, major assembly, and total direct labor hours, respectively. Also recall that Model 4 has the same dependent variable as Model 3 (total direct labor hours), but uses a proxy for the production rate variable (delivery rate to destination; e.g. B-52 Wing, as shown on DD Form 250). To insure these distinctions remain clear, each model is briefly restated prior to presentation of the test results.

Model 1. The results of Model 1 are contained in Table 5. Reduced model:

$$Y_f = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}(Y_f) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1)$$

Full model:

TABLE 5

Research Hypothesis One Results*

SRAM Model 1

Fabrication and Minor Assembly Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	1775.21	1881.92
Estimated β_1	-0.20	-0.19
Estimated β_2	--	-0.04
F Ratio	228.71	110.65
F Critical (2, 19)	--	3.52
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	.32
F Critical (1, 19)	--	4.38
Statistical Hypothesis 1B	--	Fail to Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.19
KS Critical	--	.29
Durbin-Watson Statistic	--	1.51
Durbin-Watson Crit. (d_u/d_L)	--	1.15/1.67
Criterion Test 1A	--	Passed
R^2 (Log)	.920	.921
R^2 (Actual)	.928	.927
Criterion Test 1B	--	Passed

Resid. Analysis
Mean = 3.75
KS Statistic = .189 < KS_c of .290 ∴ Normal Distrib.
Constant Variance - OK
Autocorr. - No

*Certain table values may be masked in the published version of this thesis because these data elements are considered proprietary by the manufacturer.

$$Y_f = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}(Y_f) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1) + \beta_2 \cdot \text{Log}(X_2)$$

where:

Y_f = fabrication and minor assembly direct labor hours/unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Model 2. The results of Model 2 are contained in Table 6. Reduced model:

$$Y_a = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}(Y_a) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1)$$

Full model:

$$Y_a = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}(Y_a) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1) + \beta_2 \cdot \text{Log}(X_2)$$

where:

Y_a = major assembly direct labor hours/unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

TABLE 6

Research Hypothesis One Results

SRAM Model 2

Major Assembly Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	1863.19	1890.33
Estimated β_1	-0.39	-0.39
Estimated β_2	--	-0.01
F Ratio	1796.53	855.18
F Critical (2, 19)	--	3.52
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	.04
F Critical (1, 19)	--	4.38
Statistical Hypothesis 1B	--	Fail to Reject H_0
Residual Plot	--	Unacceptable
KS Statistic	--	.09
KS Critical	--	.29
Durbin-Watson Statistic	--	1.14
Durbin-Watson Crit. (d_u/d_L)	--	1.15/1.67
Criterion Test 1A	--	Failed
R^2 (Log)	.990	.989
R^2 (Actual)	.996	.996
Criterion Test 1B	--	Passed

<u>Resid. Analysis</u>

Mean = .94

KS Statistic = .094 < KS_c of .290 ∴ Normal Distrib.

Constant variance - No - Most terms within 1 std error, but snaking pattern

Autocorr. - Indecisive

Model 3. The results of Model 3 are contained in Table 7. Reduced model:

$$Y_t = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_t) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full model:

$$Y_t = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}\ (Y_t) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

where:

Y_t = total direct labor hours/unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Model 4. The results of Model 4 are contained in Table 8. Reduced model:

$$Y_t = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_t) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full model:

$$Y_t = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}\ (Y_t) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

TABLE 7

Research Hypothesis One Results

SRAM Model 3

Total Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	3366.71	3520.65
Estimated β_1	-0.26	-0.25
Estimated β_2	--	-0.03
F Ratio	735.51	356.36
F Critical (2, 19)	--	3.52
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	.37
F Critical (1, 19)	--	4.38
Statistical Hypothesis 1B	--	Fail to Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.22
KS Critical	--	.29
Durbin-Watson Statistic	--	1.35
Durbin-Watson Crit. (d_u/d_L)	--	1.15/1.67
Criterion Test 1A	--	Passed
R^2 (Log)	.973	.974
R^2 (Actual)	.975	.975
Criterion Test 1B	--	Passed

Resid. Analysis

Mean = 3.91
KS Statistic = .222 < KS_c of .29 ∴ Normal Distrib.
Constant Variance - OK, Some resid values larger for larger values of Y_{hat}
Autocorr. - Indecisive

TABLE 8

Research Hypothesis One Results

SRAM Model 4

Total Hours Per Unit with DD250 Delivery Rate Proxy

Test Items	Reduced Model	Full Model
Estimated β_0	3184.85	3614.84
Estimated β_1	-0.25	-0.24
Estimated β_2	--	-0.06
F Ratio	927.60	464.89
F Critical (2, 40)	--	3.23
Statistical Hypothesis 1A	--	Reject H_o
F Statistic	--	1.05
F Critical (1, 40)	--	4.08
Statistical Hypothesis 1B	--	Fail to Reject H_o
Residual Plot	--	Acceptable
KS Statistic	--	.29
KS Critical	--	.29
Durbin-Watson Statistic	--	.51
Durbin-Watson Crit. (d_u/d_L)	--	1.15/1.67
Criterion Test 1A	--	Failed
R^2 (Log)	.959	.960
R^2 (Actual)	.938	.944
Criterion Test 1B	--	Passed

<u>Resid. Analysis</u>

Mean = 3.98
KS Statistic = .286 < KS_c of .290 ∴ Normal Distrib.
Constant Variance - OK
Autocorr. - Yes

where:

Y_t = total direct labor hours/unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate proxy/accounting month (delivery rate to final destination - DD250).

Research Hypothesis One Analysis Summary

As shown in Tables 5 through 8, all four models indicated a potential for supporting research hypothesis one. Very high R^2 values were evident in both the reduced and full forms of the model, thereby passing all F-tests for statistical hypothesis 1A. Both the full and reduced forms of each model proved to be significant explainers of the variation in the dependent variable; however, the production rate variable did not add significantly to this explanatory ability. The high R^2 values for the reduced model coupled with the small change in R^2 when the production rate variable was added, demonstrated the greater strength of the cumulative output variable for explaining variation in the dependent variable.

The results of the appropriateness tests were mixed. Models 1 and 3 met all assumptions while Model 2 passed the normal distribution assumption, but failed the constant variance and independent error terms tests. Model 4 did not satisfy the assumption of independent error terms.

One of the primary reasons for including Model 4 in the research was to investigate the degree of sampling error inherent in utilizing only 22 data points out of the population of 42 for SRAM. The R^2 and coefficient values in Model 4, which utilized a census of the total 42-point population, differed only slightly from those of Models 1 and 3. Therefore, the concern over possible sampling error was eased.

To summarize, two models were found appropriate for the SRAM data, Models 1 and 3. Addition of the production rate variable did not significantly increase the explanatory ability of the already strong reduced model. Research hypothesis one for the SRAM program was, therefore, not supported.

Analysis of Research Hypothesis Two

Models 1 and 3 passed the appropriateness tests and were, therefore, validated for predictability testing under research hypothesis two. Because Models 2 and 4 were not deemed appropriate under research hypothesis one, statistical inference for these models was not possible. However, the predictive ability calculations for them are presented for subjective evaluation. Even with statistical inference lacking, it may be useful to know whether or not good predictive ability results were obtained.

Analysis of the predictive ability of the SRAM models was conducted using the computer program listed in the Appendix. This program contains an option that permits the researcher to perform stepwise truncation of input data points and simulate predictions of direct labor requirements. Predicted values are compared with the observed values and any deviation is computed both as an absolute deviation and as a percentage of the observed value. Since this process is carried out simultaneously for both the full and reduced models, it permits a comparison of the predictive ability of the reduced model with the full model (16:66).

For example, if the input data base contains 22 data points (as in the case of the SRAM data), the last data point (case number 22) is truncated. One limitation of the model is that truncation cannot step backward beyond the total number of data points divided by two, plus two. So for SRAM, simulating 12 months of prediction was impossible. The maximum number of data points (months) that could be truncated for SRAM was nine (i.e., 22 ÷ 2 = 11, 11 + 2 = 13, 22 - 13 = 9, the maximum number of data points that could be truncated with 22 total data points). Continuing with the procedure, regression coefficients are computed for the full and reduced models using 22 data points and these coefficients are used to predict the direct labor requirements for case number 22. The predicted values for the full and reduced models are subtracted from the observed values and the absolute value of the resulting deviations is stored in an array for use in the test of statistical hypothesis two. The deviation is also divided by the observed value and multiplied by 100 to arrive at a percentage deviation for use in criterion test two.

The above process is repeated for case number 21 using the original data base truncated to 20, 19, . . ., etc. data points. The stepwise truncation continues until a prediction of case number 22 has been made from data points nine months prior to case number 22, and the entire procedure is repeated for cases 22 through 13. In data bases where the data points represent one-month intervals, this procedure results in 81 test situations and provides a subjective test of a model's predictive ability (16:67).

This procedure is illustrated in the third section of the Appendix which contains a computer printout of a sample situation using simulated data.

The statistical hypothesis and criterion test for research hypothesis two are summarized and restated as follows.

Research Hypothesis Two. For 12 months into the future, the predictive ability of the full model is better than the predictive ability of the reduced model.

Statistical Hypothesis Two. H_0: $|\bar{D}_R| \leq |\bar{D}_F|$; H_1: $|\bar{D}_R| > |\bar{D}_F|$. Reject H_0 if $t > t_c$ (.05).

Criterion Test Two. The model with the greater total number of good (within 10 percent) and excellent (within 5 percent) predictions over the range of all test situations will be deemed the model with the better predictive ability.

Research Hypothesis Two Analysis Summary

Tables 9 through 12 summarize the predictive ability tests conducted for Models 1 through 4 of the SRAM data. Since Models 1 and 3 were the only ones found appropriate for the data, statistical inferences were made only for them. The 12-month prediction simulation for Models 1 and 3 demonstrated

TABLE 9

Research Hypothesis Two Results

SRAM Model 1

Fabrication and Minor Assembly Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	27.40	30.16
Variance	969.64	1541.42
t Test Statistic	--	-0.49
t Critical	--	-1.72
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	81	81
Total number of excellent predictions (within 5 percent)	60	58
Total number of good predictions (within 10 percent)	67	66
Criterion Test Two	--	Passed

excellent predictive ability for both the reduced and full forms of the model. The reduced model appeared to be a slightly better predictor, but this could not be shown statistically because the computed t statistic did not exceed the t critical value for Model 1 or 3. Again, the strength of the cumulative output variable may have masked the real

TABLE 10

Research Hypothesis Two Results

SRAM Model 2

Major Assembly Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	8.71	9.45
Variance	19.61	25.61
t Test Statistic	--	-1.00
t Critical	--	-1.72
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	81	81
Total number of excellent predictions (within 5 percent)	19	18
Total number of good predictions (within 10 percent)	66	58
Criterion Test Two	--	Passed

contribution of the production rate variable to the model. The same basic results are demonstrated in Models 2 and 4, but statistical inference was not possible with them because they were deemed inappropriate under research hypothesis one.

TABLE 11

Research Hypothesis Two Results

SRAM Model 3

Total Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	30.24	33.01
Variance	871.17	1497.29
t Test Statistic	--	-0.51
t Critical	--	-1.72
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	81	81
Total number of excellent predictions (within 5 percent)	44	46
Total number of good predictions (within 10 percent)	68	67
Criterion Test Two	--	Passed

In summary, all models exhibited excellent predictive ability and passed criterion test two as a result. All models failed to reject the null hypothesis under statistical hypothesis two, so the predictive ability of the reduced and full forms of the model could not be inferred to be statistically different. Therefore, research hypothesis two was not considered supported for the SRAM data.

TABLE 12

Research Hypothesis Two Results

SRAM Model 4

Total Hours Per Unit with DD250 Delivery Rate Proxy

Test Items	Reduced Model	Full Model
Average absolute deviation	23.17	29.10
Variance	231.45	586.97
t Test Statistic	--	-2.78
t Critical	--	-1.72
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	180	180
Total number of excellent predictions (within 5 percent)	112	95
Total number of good predictions (within 10 percent)	176	161
Criterion Test Two	--	Passed

The Maverick Data

The data furnished by the Hughes Aircraft company consisted of total direct labor requirements and production history for the total Maverick missile. Full-scale production commenced April 1972 and continued without interruption through May 1978 (73 months), resulting in the manufacture of approximately 26,500 units. Because the data reflected significant fluctuation in the production rate, the program provided an excellent test situation for the research. Like SRAM, the Maverick data were broken down into several major components --fabrication, assembly, and test. Once again, this partitioning of total direct labor hours permitted evaluation of the differing effects of the production rate on these different elements of labor. The production rate and cumulative output data were based on actuals experienced in the Tucson AZ plant; thus, no proxy for the production rate was required. Also, no significant technological, production, or accounting changes occurred during the program.

One intriguing aspect of the Maverick data was the manner in which the manufacturer accounted for direct labor hours in the three categories described above. As mentioned in Chapter III, direct labor hours were segmented into two components: Unit Index and Standard Hours. On a continuing basis, Hughes conducted time and motion studies to estimate how many hours it would take to manufacture each missile under "ideal" conditions at a particular point in the production program. This estimate was called Standard Hours, and its evolution over time represented a measure of methods improvement. For each month of production, Hughes computed a Unit Index reflecting the deviation between the actual number of direct labor hours required for production and the number of hours that would be required under ideal conditions. Whenever the actual number of hours required for production achieved *the "ideal" standard*, the Unit Index was equal to one. Any value of the index greater than one reflected less than ideal performance. The evolution of the index over time represented a measure of labor improvement or learning. To calculate direct labor hours per missile, the Unit Index was multiplied by the Standard Hours. For example, assume the program is in the early stages of production, the Standard Hours are 100 hours per unit and the Unit Index 2.50 per unit (less than perfect conditions). The two are then multiplied to calculate total hours per missile of 250, each describing a different aspect of labor. As one might expect, the Unit Index, Standard Hours, and direct labor hours exhibited learning trends to varying degrees. Because of this unique accounting procedure, the researchers were able to assess the effects of the production rate on both the "labor learning" and "methods improvement" aspects of direct labor.

The raw Maverick production data were treated as described in the explanation of individual variables for each of the models presented in Chapter III. Regression analysis technique, statistical hypothesis testing, and criterion testing for research hypotheses one and two were performed in exactly the same manner as performed on the SRAM data.

Analysis of Research Hypothesis One

Once again, to insure the distinctions among models remain clear, each model is briefly restated prior to the tabular presentation of the test results.

Model 5. The results of Model 5 are contained in Table 13. Reduced model:

$$Y_f = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_f) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full model:

$$Y_f = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}\ (Y_f) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

where:

Y_f = fabrication direct labor hours/equivalent unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Model 6. The results of Model 6 are contained in Table 14. Reduced model:

$$Y_a = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_a) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full model:

$$Y_a = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

TABLE 13

Research Hypothesis One Results

Maverick Model 5

Fabrication Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	126.16	142.92
Estimated β_1	-0.13	-0.12
Estimated β_2	--	-0.04
F Ratio	241.27	131.21
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	5.58
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.13
KS Critical	--	.16
Durbin-Watson Statistic	--	1.91
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Passed
R^2 (Log)	.773	.789
R^2 (Actual)	.797	.807
Criterion Test 1B	--	Passed

Resid. Analysis

Mean = .926
KS Statistic = .129 < KS_c of .159 ∴ Normal Distrib.
Constant Variance - Yes
Autocorr. - No

or in logarithmic form:

$$\text{Log }(Y_a) = \text{Log }(\beta_0) + \beta_1 \cdot \text{Log }(X_1) + \beta_2 \cdot \text{Log }(X_2)$$

where:

Y_a = assembly direct labor hours/equivalent units/ accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Model 7. The results of Model 7 are contained in Table 15. Reduced model:

$$Y_{tst} = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log }(Y_{tst}) = \text{Log }(\beta_0) + \beta_1 \cdot \text{Log }(X_1)$$

Full model:

$$Y_{tst} = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log }(Y_{tst}) = \text{Log }(\beta_0) + \beta_1 \cdot \text{Log }(X_1) + \beta_2 \cdot \text{Log }(X_2)$$

where:

Y_{tst} = test direct labor hours/equivalent unit/ accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

TABLE 14

Research Hypothesis One Results

Maverick Model 6

Assembly Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	901.59	998.02
Estimated β_1	-0.30	-0.28
Estimated β_2	--	-0.05
F Ratio	777.93	401.41
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	3.00
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Fail to Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.33
KS Critical	--	.16
Durbin-Watson Statistic	--	.79
Durbin-Watson Crit (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Failed
R^2 (Log)	.916	.920
R^2 (Actual)	.837	.811
Criterion Test 1B	--	Passed

Resid. Analysis
Mean = -.482
KS Statistic = .3271 > KS_c Of .159 ∴ Not Normal Distrib.
Constant Variance - Yes
Autocorr. - Yes

TABLE 15

Research Hypothesis One Results

Maverick Model 7

Test Hours Per Unit

Test Item	Reduced Model	Full Model
Estimated β_0	150.84	170.37
Estimated β_1	-0.27	-0.22
Estimated β_2	--	-0.11
F Ratio	353.26	188.53
F Critical (2,70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	4.82
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.38
KS Critical	--	.16
Durbin-Watson Statistic	--	.81
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Failed
R^2 (Log)	.833	.843
R^2 (Actual)	.551	.500
Criterion Test 1B	--	Failed

Resid. Analysis

Mean = .68
KS Statistic = .381 > KS_c of .159 ∴ Not Normal Distrib
Constant Variance - Marginal, Slight Pattern Persistence
Autocorr. - Yes

Model 8. The results of Model 8 are contained in Table 16. Reduced model:

$$Y_t = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_t) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full model:

$$Y_t = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}\ (Y_t) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

where:

Y_t = total direct labor hours/equivalent unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Model 9. The results of Model 9 are contained in Table 17. Reduced model:

$$Y_{tu} = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_{tu}) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full model:

$$Y_{tu} = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

TABLE 16

Research Hypothesis One Results

Maverick Model 8

Total Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	735.62	740.27
Estimated β_1	-0.21	-0.21
Estimated β_2	--	-0.01
F Ratio	854.57	421.59
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	.05
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Fail to Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.33
KS Critical	--	.16
Durbin-Watson Statistic	--	.63
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Failed
R^2 (Log)	.923	.923
R^2 (Actual)	.850	.846
Criterion Test 1B	--	Passed

<u>Resid. Analysis</u>

Mean = -.028
KS Statistic = .329 > KS_c of .159 ∴ <u>Not</u> Normal Distrib
Constant Variance - Marginal, slight pattern
Autocorr. - Yes

or in logarithmic form:

$$\text{Log}\ (Y_{tu}) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

where:

Y_{tu} = Unit Index portion of total hours/equivalent unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Model 10. The results of Model 10 are contained in Table 18. Reduced model:

$$Y_{tsh} = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}\ (Y_{tsh}) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1)$$

Full Model:

$$Y_{tsh} = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}\ (Y_{tsh}) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

where:

Y_{tsh} = Standard Hours portion of total direct labor hours/equivalent unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month,

X_2 = production rate/accounting month.

TABLE 17

Research Hypothesis One Results

Maverick Model 9

Unit Index for Total Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	36.48	41.03
Estimated β_1	-0.19	-0.13
Estimated β_2	--	-0.10
F Ratio	399.81	237.82
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	12.28
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.32
KS Critical	--	.16
Durbin-Watson Statistic	--	.59
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Failed
R^2 (Log)	.849	.872
R^2 (Actual)	.752	.705
Criterion Test 1B	--	Failed

<u>Resid. Analysis</u>

Mean = .081
KS Statistic = .315 > KS_c of .159 ∴ <u>Not</u> Normal Distrib
Constant Variance - OK - <u>Slight Pattern</u>
Autocorr. - Yes

TABLE 18

Research Hypothesis One Results

Maverick Model 10

Standard Hours for Total Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	78.96	72.36
Estimated β_1	-0.05	-0.09
Estimated β_2	--	0.08
F Ratio	223.84	394.19
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_o
F Statistic	--	136.71
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.05
KS Critical	--	.16
Durbin-Watson Statistic	--	1.66
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Passed
R^2 (Log)	.759	.918
R^2 (Actual)	.752	.912
Criterion Test 1B	--	Passed

<u>Resid. Analysis</u>

Mean = .096
KS Statistic = .053 < KS_c of .159 ∴ Normal Distrib.
Constant Variance - Yes - Excellent
Autocorr. - No

<u>Model 11</u>. The results of Model 11 are contained in Table 19. Reduced model:

$$Y_{fu} = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}(Y_{fu}) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1)$$

Full model:

$$Y_{fu} = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

or in logarithmic form:

$$\text{Log}(Y_{fu}) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1) + \beta_2 \cdot \text{Log}(X_2)$$

where:

Y_{fu} = Unit Index portion of fabrication direct labor hours/equivalent unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

<u>Model 12</u>. The results of Model 12 are contained in Table 20. Reduced model:

$$Y_{fsh} = \beta_0 \cdot X_1^{\beta_1}$$

or in logarithmic form:

$$\text{Log}(Y_{fsh}) = \text{Log}(\beta_0) + \beta_1 \cdot \text{Log}(X_1)$$

Full model:

$$Y_{fsh} = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2}$$

TABLE 19

Research Hypothesis One Results

Maverick Model 11

Unit Index for Fabrication Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	4.82	6.82
Estimated β_1	-0.10	-0.07
Estimated β_2	--	-0.11
F Ratio	103.65	114.45
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	51.51
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.13
KS Critical	--	.16
Durbin-Watson Statistic	--	1.80
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Passed
R^2 (Log)	.593	.766
R^2 (Actual)	.662	.773
Criterion Test 1B	--	Passed

<u>Resid. Analysis</u>

Mean = .011
KS Statistic = .126 < KS_C of .160 ∴ Normal Distrib.
Constant Variance - Yes
Autocorr. - No

or in logarithmic form:

$$\text{Log}\ (Y_{fsh}) = \text{Log}\ (\beta_0) + \beta_1 \cdot \text{Log}\ (X_1) + \beta_2 \cdot \text{Log}\ (X_2)$$

where:

Y_{fsh} = Standard Hours for fabrication direct labor hours/equivalent unit/accounting month,

X_1 = cumulative output plot point (cumulative units at end of accounting month),

X_2 = production rate/accounting month.

Research Hypothesis One Analysis Summary

The regression analyses and hypotheses testing results for Maverick shown in Tables 13 through 20 indicate support for research hypothesis one. The eight models exhibited a strong inverse relationship between the dependent variable and the independent variables. Each model supported statistical hypothesis one (A) with ease. The results of testing for statistical hypothesis one (B) in every model, except Models 6 (assembly) and 8 (Total hours/missile), demonstrated that the explanatory power added by the production rate variable was statistically significant at the 0.05 level of significance. Only Models 7, 9, and 12 did not have R^2 (Actual) values greater than 0.75 under criterion test one (B).

Notwithstanding these excellent results, only Models 5 (fabrication), 10 (standard hours for total hours), and 11 (unit index for fabrication) were found appropriate for the Maverick data. Model 10 achieved the most spectacular results.

TABLE 20

Research Hypothesis One Results

Maverick Model 12

Standard Hours for Fabrication Hours Per Unit

Test Items	Reduced Model	Full Model
Estimated β_0	26.25	21.00
Estimated β_1	-0.03	-0.05
Estimated β_2	--	0.07
F Ratio	2.58	32.23
F Critical (2, 70)	--	3.15
Statistical Hypothesis 1A	--	Reject H_0
F Statistic	--	35.43
F Critical (1, 70)	--	4.00
Statistical Hypothesis 1B	--	Reject H_0
Residual Plot	--	Acceptable
KS Statistic	--	.15
KS Critical	--	.16
Durbin-Watson Statistic	--	1.80
Durbin-Watson Crit. (d_u/d_L)	--	1.55/1.67
Criterion Test 1A	--	Passed
R^2 (Log)	.035	.479
R^2 (Actual)	.027	.463
Criterion Test 1B	--	Failed

Resid. Analysis

Mean = .065
KS Statistic = .154 < KS_c of .160 ∴ Normal Distrib.
Constant Variance - Marginal
Autocorr. - Marginal

The other models either failed the KS test for normality of residuals, the Durbin-Watson test for autocorrelation of residuals, the constant variance test, or a combination of these tests.

In summary, the results supported research hypothesis one for the Maverick data. All eight models were then tested for predictive ability under research hypothesis two, with statistical inference applying only to appropriate models (Models 5, 10, and 11).

Analysis of Research Hypothesis Two

The predictive ability analysis of the Maverick models (Models 5 through 12) was conducted in the same manner as described for the SRAM data. The 73 data points in the Maverick data permitted a more realistic simulation scenario than for SRAM. The researchers assumed, for purposes of simulation, that the Maverick program had completed 48 months of production and wished to estimate the next 12 months' direct labor requirements. Data points 49 through 73 were, therefore, truncated and regression was performed on points 1 through 48 to predict the hours for each of the next 12 months (points 49 through 60).

Research Hypothesis Two Analysis Summary

Tables 21 through 28 summarize the predictive ability tests conducted for Models 5 through 12 of the Maverick data. Since Models 5, 10, and 11 were the only ones found appropriate

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TABLE 21

Research Hypothesis Two Results

Maverick Model 5

Fabrication Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	2.26	5.05
Variance	3.19	6.61
Z Test Statistic	--	-15.41
Z Critical	--	-1.65
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	145	48
Total number of good predictions (within 10 percent)	213	94
Criterion Test Two	--	Failed

for the data, statistical inferences were made only for them. Model 10 (Standard Hours portion of total hours) exhibited the best results. The average absolute deviation of the predicted values from the actuals for the full model was about half of that for the reduced model. The full model's superior predictive ability was found to be statistically significant

TABLE 22

Research Hypothesis Two Results

Maverick Model 6

Assembly Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	5.98	6.88
Variance	14.35	50.73
Z Test Statistic	--	-1.93
Z Critical	--	-1.65
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	50	79
Total number of good predictions (within 10 percent)	104	128
Criterion Test Two	--	Failed

at the 0.05 level of significance. It was also found to be a practical predictor with 192 out of 300 test situations falling in the good range (within 10 percent). Meanwhile, the reduced model had only 8 out of 300 predictions within 10 percent of the actuals. Models 5 and 11 both found the better predictor to be the reduced model in terms of

TABLE 23

Research Hypothesis Two Results

Maverick Model 7

Test Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	8.92	7.38
Variance	41.46	37.16
Z Test Statistic	--	2.99
Z Critical	--	1.65
Statistical Hypothesis Two	--	Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	99	119
Total number of good predictions (within 10 percent)	143	200
Criterion Test Two	--	Passed

statistical significance. However, both the reduced and full models generally did not prove very practical, with few predictions in the "good" range. The reduced form under Model 5 was the exception, getting half of the predictions in the "excellent" range and two-thirds in the "good" range overall.

Several observations are warranted for the models not

TABLE 24

Research Hypothesis Two Results

Maverick Model 8

Total Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	8.92	7.38
Variance	41.46	37.16
Z Test Statistic	--	2.99
Z Critical	--	1.65
Statistical Hypothesis Two	--	Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	99	119
Total number of good predictions (within 10 percent)	143	200
Criterion Test Two	--	Passed

deemed appropriate under research hypothesis one (Models 6-9 and 12). These observations are presented with caution since statistical inferences cannot be made with inappropriate models. However, a model may be statistically inappropriate but prove to be a good predictor from a practical standpoint. This was the case for Models 7 (test hours) and 8 (total hours).

TABLE 25

Research Hypothesis Two Results

Maverick Model 9

Unit Index for Total Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	0.60	1.01
Variance	0.18	0.32
Z Test Statistic	--	-9.94
Z Critical	--	-1.65
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	77	26
Total number of good predictions (within 10 percent)	171	64
Criterion Test Two	--	Failed

The full form of both models had 119 out of 300 predictions in the "excellent" range and 200 in the "good" range overall. Six of the eight models consistently demonstrated the full model to have the better, and more practical, predictive ability. Consequently, one could not refute the better predictive ability of the full model from a "real world,"

TABLE 26

Research Hypothesis Two Results

Maverick Model 10

Standard Hours for Total Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	6.86	3.98
Variance	1.42	2.01
Z Test Statistic	--	26.91
Z Critical	--	1.65
Statistical Hypothesis Two	--	Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	0	37
Total number of good predictions (within 10 percent)	8	192
Criterion Test Two	--	Passed

practical standpoint.

In summary, because of the superior results achieved by the full form of the model for the appropriate models (5, 10, and 11) and the better practical predictive ability exhibited by the full form for the remaining inappropriate models, research hypothesis two was considered supported for

TABLE 27

Research Hypothesis Two Results

Maverick Model 11

Unit Index for Fabrication Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	0.28	0.34
Variance	0.02	0.03
Z Test Statistic	--	-4.76
Z Critical	--	-1.65
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent)	3	5
Total number of good predictions (within 10 percent)	83	53
Criterion Test Two	--	Failed

the Maverick data.

Comparative Analysis and Summary

The results of regression analysis on the twelve models tested revealed marked similarities and differences between the SRAM and Maverick data. The common and unique features of each program are discussed. A summary of the research findings

TABLE 28

Research Hypothesis Two Results

Maverick Model 12

Standard Hours for Fabrication Hours Per Unit

Test Items	Reduced Model	Full Model
Average absolute deviation	2.81	5.55
Variance	0.42	17.77
Z Test Statistic	--	-11.12
Z Critical	--	-1.65
Statistical Hypothesis Two	--	Fail to Reject H_0
Total number of test situations	300	300
Total number of excellent predictions (within 5 percent	0	68
Total number of good predictions (within 10 percent)	31	108
Criterion Test Two	--	Passed

and evaluation of the applicability of the production rate model to the data sets complete Chapter IV.

Comparative Analysis

The Maverick and SRAM production data exhibited several common characteristics. Both data sets covered the entire production history for their respective programs, from commencement of full-scale production to complete or near-complete phase-down. Both were long-running programs; 42 months for SRAM and 73 months for Maverick. Both production programs occurred during basically the same time frame, the mid-1970s. As a result, they both utilized the production technology and processes prevalent in the industry at that time. Finally, a most fortunate common feature was meeting the basic assumptions of learning curve models. Neither program experienced any significant changes in production technology, missile design, or accounting procedures.

While the similarities between the two programs enhanced the researchers' ability to apply the findings to missile production programs in general, the differences added depth to the analysis. One of the primary factors affecting the outcome of the analysis was the labor/capital mix of the programs. The SRAM data reflected production operations at the Boeing plant, which consisted of minor and major assembly with very little fabrication. Hence, the SRAM program was a labor-intensive effort. Conversely, the Maverick program was characterized by capital-intensive operations; i.e. much fabrication performed in-house along with assembly and test. As a result, the SRAM program exhibited generally steeper slopes for the model coefficients.

Two other differing aspects of the programs were the production quantities and variation in production rate. SRAM production was for 1,500 units while Maverick was for about 26,500. One would expect mass production techniques to apply to Maverick, with SRAM more toward the batch production methodology end of the spectrum. The production rate requirement for SRAM was 40 units per month throughout the program. Although plant actuals varied from this goal, a 40-unit delivery rate was maintained for the bulk of the program. In contrast, the Maverick program exhibited a much less stable production rate throughout the program. Because the SRAM program had a more stable production rate, one would expect the contribution of the production rate variable to the explanatory ability of the model to be less for SRAM than Maverick. The analysis supported this intuitive notion and will be discussed in detail later.

Summary

The preceding analyses of the two missile production programs were based on the methodology and data treatment as described in Chapter III. As shown in Table 29, five out of the twelve models tested were found appropriate for the data, Models 1 and 3 for SRAM and 5, 10, and 11 for Maverick. Of those five, only three (all Maverick models) supported research hypothesis one. The contribution of the production rate variable to the explanatory ability of the model was difficult to assess for the SRAM data because of the already strong relationship between the cumulative output variable and the direct labor variable. With R^2 (actual) values for the reduced model already in the high .90s, there was little room for improvement in spite of the good R^2 (actual) values

TABLE 29

Change In R^2 (Actual) For All Twelve Models Tested After Inclusion of Production Rate

Model	R^2 Reduced	R^2 Full	ΔR^2
1 (Fab/Assy)*	.928	.927	-.001
2 (Maj.Assy)	.996	.996	.000
3 (Total/Act.)*	.975	.975	.000
4 (Total/Deliv)	.938	.944	.006
5 (Fab.)*	.797	.807	.010
6 (Assy.)	.837	.811	-.026
7 (Test)	.551	.500	-.051
8 (Total)	.850	.846	-.004
9 (Unit Index Tot)	.752	.705	-.047
10 (Std.Hr.Total)*	.752	.912	.160
11 (Unit Index Fab)*	.662	.773	.111
12 (Std.Hr. Fab)	.027	.463	.436

*These models were found appropriate for the data. All others were found inappropriate.

for the production rate variable alone (.70s and .80s). In contrast, the models for the Maverick data revealed that the production rate variable was an important explainer of variation in direct labor requirements. R^2 (actual) increased 1 percent for Model 5, 16 percent for Model 10, and 11 percent for Model 11. Other models showed slight decreases in

R^2 (actual) values while Model 12 attained a spectacular increase of 44 percent; however, statistical inferences could not be made with confidence with these models because they did not pass the appropriateness tests.

Research hypothesis two was not accepted for the SRAM data, but was accepted for the Maverick data. The simulation showed that the appropriate SRAM models (1 and 3) were excellent predictors over the selected range of data points, but there was no statistical difference between the strength of the reduced and the full forms of the model. The appropriate Maverick models (5, 10, and 11) were shown to have varying predictive abilities. The full form of Model 10 clearly demonstrated superior predictive capability, both statistically and practically. On the other hand, Model 5 revealed the reduced model to be better, while Model 11 produced inconclusive results. The other Maverick models, though not appropriate for the data, showed the better predictor to be the full model from a practical standpoint in almost every case. In summary, the support for research hypothesis two was not overwhelming, but significant enough to be accepted without reservation.

A major finding of the analysis was the smoothing effect the addition of the production rate variable had on autocorrelation of the residuals. A Durbin-Watson statistic was computed for the reduced model, full model, and "production rate variable alone" form of the reduced model. Larger values of the statistic indicated less autocorrelation, and vice-versa.

As shown in Table 30, the reduced form of all twelve models has unacceptable or indecisive autocorrelation. The addition of the production rate variable in the full model significantly reduced this severe autocorrelation problem, increasing the number of appropriate models from zero to three and raising two others into at least the marginal range. The strong residual smoothing effect of the production rate variable was clear. When it was substituted for the cumulative output variable in the reduced form of the model, almost all autocorrelation disappeared, increasing the number of appropriate models from zero to nine out of twelve. The decrease in autocorrelation problems for the full model was attributed to this phenomenon.

An intriguing discovery by the researchers may explain why this phenomenon occurred. A widely used method for decreasing autocorrelation is the "method of first differences" (11:649). The procedure entails taking the "first differences" of all variables in the model. In other words, for a column of data listed in time series, subtract the first number in the column from the second number in the column to compute a new "first difference" value. Then proceed down the column to obtain a new column of "first difference" transformed numbers. This is exactly the way the production rate variable is calculated. The production rate is the "first difference" of the cumulative output. For example, if the number of units produced the first month is 50, the cumulative output is 50 and the production rate is 50. If 60 more units are produced

TABLE 30

Durbin-Watson Statistics

Model	Reduced Model	PRODRATE Variable Alone	Full Model
1	1.30**	3.11***	1.51**
2	1.07*	2.80***	1.14*
3	1.09*	3.22***	1.35**
4	.43*	1.07*	.51*
5	1.34*	2.18***	1.91***
6	.86*	2.24***	.79*
7	.93*	.80*	.81*
8	.61*	.76*	.63*
9	.69*	.56*	.59*
10	.23*	1.70***	1.66***
11	.81*	2.15***	1.80***
12	.49*	2.01***	1.08*

*Autocorrelation present; statistic less than d_L table values.
**Indecisive; statistic between d_L and d_u table values.
***Neither autocorrelated nor indecisive; statistic greater than d_u table values.

the second month, then the cumulative output is 110 and the production rate for that month is 60. The "first difference" for the second month would be 110 minus 50, or 60 units. Since the production rate is the "first difference" of the cumulative output, this may very well explain why the addition of the production rate to the model significantly reduced the severe autocorrelation problems with the reduced form of the model.

Another observation concerned the sensitivity of the regression coefficients, as summarized in Table 31. For all twelve models tested the mean change in β_0 from the reduced to the full model was about 12 percent with a 10 percent standard deviation. The β_1 coefficients reflected even more variability with a mean change of about 18 percent and standard deviation of 20 percent. These results indicated that even within a particular program, the coefficients were sensitive. This sensitivity suggests that development of general cost models using coefficients derived from several missile production programs is inappropriate.

An interesting sidelight of the research was the partitioning of the Maverick direct labor data into two components, the Unit Index (labor improvement) and Standard Hours (methods improvement). Tables 29 and 30, shown earlier, do not indicate any significant trends or differences for the two categories in the respective models (9 through 12). Table 31 does point out a pattern in the slope of the coefficients. The Unit Index coefficients (Models 9 and 11) consistently demonstrated much steeper slopes than the Standard Hours (Models 10 and 12). This indicated that more of the learning improvement was due to labor learning than methods improvement.

The analysis of the SRAM and Maverick production programs thus met the objectives of the research in determining

TABLE 31

Model Coefficient Variability

Model	β_0 Reduced	β_0 Full	$\Delta\beta_0$ (%)	β_1 Reduced	β_1 Full	$\Delta\beta_1$ (%)	β_2
1	1775	1882	6	-.20	-.19	-5	-.04
2	1863	1890	1.4	-.39	-.39	0	-.01
3	3367	3521	4.6	-.26	-.25	-3.8	-.03
4	3185	3615	13.5	-.25	-.24	-4	-.06
5	126	143	13.4	-.13	-.12	-7.7	-.04
6	902	998	10.6	-.30	-.28	-6.6	-.05
7	151	170	12.6	-.27	-.22	-18.5	-.11
8	735	740	.5	-.21	-.21	0	-.01
9	37	41	10.8	-.19	-.13	-31.6	-.10
10	79	72	-8.9	-.05	-.09	44.4	.08
11	4.8	6.8	41.7	-.10	-.07	-30.0	-.11
12	26	21	-19.2	-.03	-.05	66.6	.07
Mean $\Delta\beta$ -			11.93			18.18	
Std. Dev. -			10.36			20.08	

the effect of production rate variation on direct labor requirements for missile production as well as evaluating the predictive ability of the cumulative production and production rate model. Of the two programs analyzed, only the Maverick program passed all tests.

CHAPTER V

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Air Force managers attempting to plan the acquisition, operation, and maintenance of major weapon systems face an increasing array of obstacles. Inflation, spiraling cost of energy, questionable availability of energy, increased foreign competition, and international political instability have created a great deal of uncertainty. While the task has perhaps never been more difficult than now, the need for accurate cost estimating is obvious. Without accurate cost predictions, effective budgeting is severely hampered.

One of the most significant cost elements in a major system acquisition is direct labor. Experience has shown that direct labor costs are most often estimated using learning curve techniques.

Summary

Literature Review

Learning curve models were in use as early as the 1920s. Widespread interest was generated as a result of the aerospace industry's experience during World War II. Since then, numerous variations of the basic learning curve model have been investigated. With budgetary and political controls causing program accelerations and decelerations, the variation that has much promise for DOD application is the model that considers the effect of production rate variations.

As Chapter II indicated, most of the research on the effect of production rate changes concluded that production rate is a significant determinant of direct labor costs. Several years ago, Smith developed a learning curve model that included a production rate variable. The model was tested on DOD airframe programs and yielded promising results. Since then, Smith's model has been applied to other airframe programs, avionics, engines, and has now been extended to air-launched missiles.

The Model

The production rate model, which Smith called the full model, is presented as follows:

$$Y = \beta_0 \cdot X_1^{\beta_1} \cdot X_2^{\beta_2} \cdot 10^e$$

where the variables, in general terms, are described as follows:

- Y represents direct labor hours,
- X_1 represents cumulative output,
- X_2 represents the production rate,
- e represents the variation which remains unexplained by the variables in the model, and
- $\beta_0, \beta_1, \beta_2$ are regression coefficients.

To facilitate regression analysis, the model is linearized using logarithms as follows:

$$\text{Log } Y = \text{Log } \beta_0 + \beta_1 \text{ Log } X_1 + \beta_2 \text{ Log } X_2 + e$$

The reduced model referred to in this research is simply the basic learning curve model. It is identical to the full model, before and after logarithmic transformation, except that the reduced model does not include the production rate variable (6:89).

Research Objectives

As stated in Chapter I, the three objectives of this research were: 1) to determine how changes in the production rate affect total direct labor hour requirements per missile, 2) to determine how the full model compares with the reduced model as a predictor of direct labor hour requirements for continuing missile production, and 3) to determine if Smith's model is applicable to missile production.

Methodology

Linear regression analysis of the logarithmic forms of the full and reduced models was employed to achieve the research objectives. Data were obtained from two missile production programs, SRAM and Maverick. As in previous research, the data from each program required individual treatment. Data treatment is described in Chapter III. Twelve specific models were developed and then statistically analyzed under the research hypotheses.

Research hypothesis one stated that the production rate explains a significant amount of the variation in direct labor requirements for missile production. Two statistical tests and two criterion tests were employed respectively. The first statistical test was an F-test to determine if a relationship existed between the dependent variable (labor hours) and the independent variables (cumulative output and production rate). The second statistical test was another F-test to determine the production rate variable's ability, when combined with the cumulative output variable, to explain additional variation in the dependent variable.

The first criterion test then evaluated the error terms in the model for constant variance, independence, and normal distribution. The second criterion test required R^2 (actual) to be greater than or equal to .75, an arbitrary measure of the model's ability to explain a sufficient amount of variation in the dependent variable (6:91). Any model that passed both statistical and both criterion tests was considered appropriate for further testing under research hypothesis two.

Research hypothesis two stated that the production rate model predicts direct labor requirements better than the basic learning curve model. One statistical test and one criterion test were used to evaluate this hypothesis. A stepwise truncation procedure was employed to simulate the model's ability to predict direct labor requirements for the next 12 months. The last 12 data points (months) were omitted and then predicted using the simulation procedure. The statistical test consisted of a t-test or a Z-test to determine if the average absolute deviation of the full model was significantly less than that of the reduced model over the 12-month interval. The criterion test compared predicted values to the actual observed values and classified the deviations into categories. Thus, a practical measure of the amount of deviation in both the full and reduced models was achieved.

Research objective three (determine if Smith's model applies to missiles) was subjectively evaluated using the results of the hypothesis testing for all 12 models developed from the data.

Conclusions

The three primary conclusions of this research relate directly to the research objectives. First, the production rate was found to explain a significant amount of variation in direct labor hours in nine of the twelve models examined. Of these nine, only five cases were found appropriate for the data. Three of the twelve cases passed all tests in support of research hypothesis one. While not all cases supported the first research objective, enough support was evident to conclude that the production rate variable should be considered when evaluating missile production programs.

Second, the results of the predictive ability comparison were mixed. The predictive ability of the full model was excellent for all four SRAM cases. However, the predictive ability of the reduced model was approximately equal because of the overwhelming effect of the cumulative output variable in the SRAM program. Five of the eight Maverick cases clearly showed that the full model predicted direct labor requirements better than the reduced model. Of the three Maverick cases that were statistically appropriate under research hypothesis one, one case showed superior results for the full model, one case showed the reduced model to be a better predictor, and one case was inconclusive. Results for the second research objective indicate that the superiority of the full model for prediction depends on the particular program and circumstances. The beauty of Smith's model is that the user is given an indication of how well the model is likely to predict in a given situation without having to actually wait a year to determine the outcome.

Third, as a result of the hypothesis testing, the authors have concluded that Smith's model has widespread potential for missile production programs and merits additional study. Further, this research represents the fifth application of Smith's model to various aspects of DOD aerospace programs. All five research efforts have yielded positive results in at least part of the programs selected for study. Table 32 summarizes the general areas that have been investigated, and shows the average increase in the amount of direct labor variation explained by using the full model. In every case, additional variation has been explained (the average increase in explained variation over all five studies was 11.3 percent).

An 11 percent improvement in the accuracy of labor estimates could result in substantial savings on large-dollar programs. An added benefit could be enhanced credibility for

TABLE 32

Mean (Average) Changes in R^2 (Actual) For

All Research Programs Using

Smith's Production Rate Model

Area of Application	Researchers	Average R^2 Actual Reduced	Average R^2 Actual Full	Average ΔR^2
Airframes	Smith	.818	.916	.098
Airframes	Congleton/Kinton	.912	.953	.041
Avionics	Stevens/Thomerson	.491	.773	.282
Engines	Crozier/McGann	.402	.496	.094
Missiles	Allen/Farr	.755	.805	.050

DOD personnel who must present budgetary requirements to Congress. In any event, these initial successes justify the application of Smith's model to other systems and subsystems in the aerospace industry. Three additional conclusions resulted from this research and are discussed next.

Additional Conclusions

As in all previous research, the regression coefficients developed through regression analysis for a particular data set were unique to that data set. The coefficients are sensitive to almost any kind of change in a program, even from month to month within the same program. Therefore, a general model cannot be developed that applies to all missile production programs.

As described in Chapter IV, the addition of the production rate variable tended to smooth any autocorrelation that was present in the data. This phenomenon occurs because the production rate is in effect the "first difference" of the cumulative output. This smoothing effect adds a distinct advantage to the full model.

Finally, several of the cases studied during this research yielded models that were statistically inappropriate for the data. Whenever a user encounters this predicament, alternative methods of estimating should not be forgotten. Exponential smoothing, moving averages, and trend analysis are examples of estimating techniques that can be performed easily with a hand calculator.

Recommendations

The production rate model is available to users in the Copper Impact Library under the file name PRODRATE. With the model available and substantial success in five research efforts, the Air Force should emphasize use of the model on actual production programs. The model has potential application anywhere that learning curve theory applies.

A related recommendation is that a checklist guide to the practical use of the model be developed. Such a guide would encourage use of the model by those who are uneasy with statistics and the seeming complexity of the model.

Finally, further research efforts are recommended for other major aerospace systems and subsystems. For instance, this research investigated air-launched missiles built with the early 1970's technology. Other applications might include ground- and sea-launched missiles as well as other air-launched missiles produced with more recent technology.

APPENDIX

THE COMPUTER PROGRAM PRODRATE

This appendix is made up of three sections. The first section describes how the computer program PRODRATE works and the improvements made by the authors. The second section lists the revised program in its entirety. Finally, the third section presents a sample run of simulated test data.

The PRODRATE Program and the Improvements

Numerous multiple linear regression programs containing a wide variety of options were available for this research. As in the previous research efforts by Smith and the others that followed (reference Chapter II), the computer program written by Smith (15:147-153) proved to be the best tool for accomplishing the research objectives. Most regression computer programs calculated the customary R^2 values, coefficients, and other regression statistics, but did not provide an assessment of model predictability, which was one of the primary areas of interest. PRODRATE contained a user option that printed a listing of actual direct labor requirements, predicted direct labor requirements, the resulting residuals, and statistics for predictability comparisons. This feature was unique and was one the authors found unavailable elsewhere.

Notwithstanding the desirable characteristics of PRODRATE, it did have several undesirable ones. Stevens and Thomerson modified the program extensively (16:109-142) to make it more usable for cost analysts using the COPPER IMPACT computer system.[3] Their improvements greatly enhanced the program's overall usability, but left several serious drawbacks unchanged. Residual analysis for model appropriateness is essential for multiple linear regression analysis. The revised version of PRODRATE had no such analysis capability, forcing the user to rely on subjective, manual analysis or computer programs on other systems. As a result, much additional time and effort had to be expended doing manual plots or duplicating data bases for use on other computer systems. Other drawbacks included long, more expensive running time and a need for more program output flexibility.

Because of these undesirable features, the authors, with the assistance of Captain Tom Sandman of the Continuing Education Department in the AFIT School of Systems and Logistics, modified the PRODRATE program to add residual analysis statistics, improve running time, and increase program usability. These changes definitely saved considerable time and effort in conducting the research and will, hopefully, do the same for future PRODRATE users.

Before the specific program improvements can be addressed, a description of what the program does is in order. Stevens and Thomerson described how PRODRATE works in the following manner:

---

[3]COPPER IMPACT is the project name of an Air Force program to Improve Modern Pricing And Costing Techniques in the contracting process. The time-sharing computer system is designated by the same name, COPPER IMPACT, and is currently government-leased from General Electric.

The program reads the input data from any file specified by the user. Instructions on how to build a data file are available in the program. This feature allows the user to change the form of the model (e.g., unit curve, cumulative curve, total cost curve) simply by making the necessary modifications to the data base. In addition, an option within the program allows the user to list the input data as they were read from the data file and converted to logarithms.

Analysis of the data is begun by calculating and printing the Pearson correlation coefficients of the three variables: direct labor requirements, cumulative production, and production rate. Log-linear regression is first performed between the direct labor requirements (dependent) variable and the cumulative production (independent) variable. Finally the dependent variable is regressed against both independent variables simultaneously.

In presenting the results of each of these three regressions, the program prints a listing of the actual direct labor requirements, the predicted direct labor requirements, and the residuals. This feature of PRODRATE is one the authors found unavailable elsewhere. The obvious advantage is that the user can relate the results to the original untransformed variable (rational numbers, not logarithms) and see how well the untransformed data fit the model.

Following the listing of the residuals, summary statistics are printed for each model. They include the values for the coefficients (exponents), standard errors, F ratios, R^2, R^2 (actual), and learning factor. Two selective options for which additional printouts are available are the Predictive Ability Tests and the Projection and Sensitivity Matrix. For a quick-look analysis of several different models, the program can be preset to stop after three regression analyses by not selecting the additional options.

The Predictive Ability Test option permits the user to select the number of data points (cases) to be truncated during the test and thus, control the time span over which the test is conducted. The test is performed using nested DO loops to perform a stepwise truncation of the data points. The truncated data is then predicted using the regression results of the remaining data. After all truncated cases have been predicted and results printed, a summary table is printed. This summary table contains data on statistical significance and permits subjective comparisons of the accuracy of predictions made by the full and reduced models. . . .

The Projection and Sensitivity Matrix option of program PRODRATE provides the cost and price analyst with a means of predicting direct labor requirements at varying production rates. This option also permits the user

> to see the sensitivity of the direct labor requirements to changes in production rate over a wide range of cumulative production. The last observed values for cumulative production and the production rate are used as the starting point for this projection. The cumulative production variable is increased by increments of 1 percent of the last observed value, while the production rate variable begins at 70 percent of the last observed value and is increased by 10 percent increments until it reaches 150 percent of the last observed value.
>
> These projections are printed in matrix form with the projected production rates printed across the top of the matrix and the projected cumulative production plot points printed along the left margin of the matrix. Projected direct labor requirements can then be read directly from the matrix by matching a given production rate with a given number of cumulative units. The value for direct labor requirements is found at the intersection of the corresponding row and column.
>
> In summary, therefore, the program PRODRATE is a modified version of Smith's FORTRAN IV program. Like Smith's program, PRODRATE converts the input data to logarithms prior to regression. In addition, PRODRATE permits the user to automatically receive or decline either or both of the options for Predictive Ability Tests and Projection and Sensitivity Matrices. For the analyst who is accustomed to working with the learning curve model, the program PRODRATE quickly shows whether the production rate variable is significant and the effect it has on estimating direct labor requirements. The authors believe the program PRODRATE can be a very useful tool for the government cost and price analyst [16:110-114].

Having described how the basic PRODRATE program works, the improvements made by the authors can now be addressed. As mentioned earlier, the modifications were made to accomplish three objectives: provide statistics to determine appropriateness of the regression models, reduce expensive run-time, and increase program usability. How these objectives were accomplished will now be discussed.

As stated in Chapter III, each regression model had to satisfy three assumptions to be deemed appropriate for the data and valid for statistical inference. The residuals had to be normally distributed, have a constant variance, and be statistically independent. The PRODRATE program had no built-in tests for these assumptions, but the COPPER IMPACT system library did. The library contained a statistical package called STATII***, which possessed the necessary residual testing capability. However, PRODRATE did not store the model residuals for analysis by other computer programs. The authors modified PRODRATE to store the computed residuals and fitted dependent variable values for each model, thus making possible the use of the powerful STATII*** package.

The STATII*** package contained a routine called STAT1 that computed a Kolmogorov-Smirnov (KS) statistic for determining if a population was normally distributed. The authors ran the stored residual values from each PRODRATE-generated model through the STAT1 routine to obtain the KS statistic used in the KS test for normality of the residuals.

The constant variance assumption was evaluated using the Plot routine under STATII***. Similar to the methodology used in the KS test, the stored residuals were plotted (by the computer) versus the stored fitted dependent variable values for each model run through PRODRATE. The authors were then able to ascertain by subjective analysis if the plot demonstrated a reasonably constant, random variance with no noticeable persistence.

The STATII*** system also contained a Durbin-Watson test capability for independence of the residuals. However, the test was buried in an expensive multiple regression routine. Since the test procedure was relatively simple to program, the authors chose to modify PRODRATE to compute a Durbin-Watson statistic for each model. This approach avoided the need for costly computer time under STATII*** and gave PRODRATE a built-in capability to test for autocorrelation at a much lower cost.

These modifications to PRODRATE to store computed residuals with fitted dependent variable values and provide Durbin-Watson statistics greatly facilitated the research. They permitted use of a powerful statistical package on the same computer system as PRODRATE and provided a residual analysis capability in PRODRATE itself, which was not possible before. These improvements eliminated the need for tedious manual analysis and/or time-consuming transfer of raw regression data files to other computer systems.

Several PRODRATE modifications were made to decrease run-time and increase model flexibility. The specific changes included transformation of the program from FORTRAN IV into machine-readable code, addition of an option to suppress the full printout, and an option for more detailed specification of truncation parameters in the short-range prediction routine. Each of these refinements will be discussed separately.

Because the basic version of PRODRATE was stored in the COPPER IMPACT system in FORTRAN IV language instead of machine language, users were being charged for compilation each time the program was run. They also had a short waiting period for program execution while the program was being compiled. By transforming PRODRATE into a machine-executable form, these unnecessary charges and delays were eliminated.

As described earlier, PRODRATE prints the observed, predicted, and residual values for each model in the run. It also prints a detailed series of matrices under the short-range prediction option. One complete run of PRODRATE with this printout format takes about 35 minutes. The authors found this level of printout detail often unnecessary. Therefore, an option was added to the program for the user to elect a full or abbreviated printout. The abbreviated version eliminated listing of observed, predicted, and residual values as well as the intervening prediction matrices. When the abbreviated format was used, the run-time was reduced from 35 minutes to 3 minutes. Only the key summary tables were printed with a reduction of printouts from approximately ten pages to one page. The time and computer cost savings are obvious. The last section of this appendix shows comparative outputs of the full and abbreviated formats.

The short-range prediction option lacked the needed flexibility for the prediction simulation used in the research. As described in Chapters III and IV, the objective was to simulate "real world" use of PRODRATE. Many users are a number of months into production and wish to forecast direct labor requirements for the next fiscal year. The basic version of PRODRATE allowed simulation only at the end of the production program (where "toe-up" often occurs), and had no capability to simulate a period earlier in production. As a result, the authors added an option for the user to specify the simulated time period anywhere in the last half of the production program. This feature added the needed flexibility to meet user needs.

In summary, the revised version of PRODRATE developed in this research significantly reduced user costs and program usability. PRODRATE users can now perform essential residual analysis with the additional PRODRATE statistics and the statistical packages already in the COPPER IMPACT system. In addition, several options are now available to drastically decrease run-time and increase the usability of the prediction routines.

Listing of the Revised PRODRATE Program

This section lists the computer program PRODRATE in its entirety. The original program was developed by Lt. Col. Larry L. Smith, and later modified by Capt. David Y. Stevens. The version listed incorporates the original program and all modifications, including those added by this research. The actual program used during this research is the program presented in this section.

```
100C****************************************************************************************************
110C
120C     PPPPP  RRRRR  OOOOO  DDD    RRRRR  AAAAA  TTTTT  EEEEE
130C     P   P  R   R  O   O  D  D   R   R  A   A    T    E
140C     PPPPP  RRRRR  O   O  D   D  RRRRR  AAAAA    T    EEE
150C     P      R  R   O   O  D  D   R  R   A   A    T    E
160C     P      R   R  OOOOO  DDD    R   R  A   A    T    EEEEE
170C
180C****************************************************************************************************
190C
200C                THE CUMULATIVE PRODUCTION AND PRODUCTION RATE COST MODEL
210C
220C     THE ORIGINAL PROGRAMMER IS LT COL LARRY L. SMITH [AFIT/LSGM AV# 785-5096] - JAN 1978
230C     LATER MODIFIED BY CAPT DAVID Y. STEVENS [ESD/PKG AV# 478-3462] -JUNE 1979
231C     THIS MODIFIED VERSION WAS PROGRAMMED BY CAPTS SCOTT ALLEN, TOM SANDMAN, AND
232C     MIKE FARR [ASD/PM, AFIT LS, AND ASD/PM, RESPECTIVELY] -JUNE 1980
240C****************************************************************************************************
250 5 FORMAT(1H1,//,100("*"),//,1X,40X,"PRODRATE INSTRUCTIONS",//,1X,100("*"),//,
260& "      THIS PROGRAM IS DESIGNED TO EVALUATE THE VARIATION IN DIRECT LABOR REQUIREMENTS AS A ",/,
270& " FUNCTION OF CUMULATIVE PRODUCTION AND PRODUCTION RATE.  IN ADDITION, THE ANALYST MAY ",/,
280& " COMPARE THE RESULTS OBTAINED FROM THE STANDARD LEARNING CURVE WITH THE RESULTS OBTAINED ",/,
290& " FROM THE CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL.  THE COST MODELS USED IN THIS ",/,
300& " PROGRAM ARE:",//,
310& "      1.  REDUCED MODEL [STANDARD LEARNING CURVE MODEL]",//,
320& "              Y = B0 + (X1 ** B1) + (10 ** E)",//,
330& "      2.  FULL MODEL [CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL]",//,
340& "              Y = B0 + (X1 ** B1) + (X2 ** B2) + (10 ** E)",//,
350& "         WHERE: Y                IS THE DIRECT LABOR REQUIREMENTS",/,
360& "                X1               IS THE CUMULATIVE PRODUCTION PLOT POINT",/,
370& "                X2               IS THE PRODUCTION RATE PROXY(E.G. EQUIVALENT UNITS PER MONTH)",/,
380& "                E                REPRESENTS THE ERROR TERM",/,
390& "                B0, B1, AND B2  ARE  PARAMETERS DETERMINED BY REGRESSION",//,
400& "      DATA ARE INPUT BY READING FROM ANY PROPERLY FORMATTED DATA FILE.  YOUR DATA FILE SHOULD ",/,
410& " BE SAVED TO ANY PERMANENT FILENAME.  YOU WILL BE ASK TO INPUT THE NAME OF YOUR DATA FILE ",/,
420& " AT THE APPROPRIATE STEP IN THE PROGRAM.  THE NAME OF YOUR DATA FILE CAN NOT EXCEED 8 ",/,
430& " CHARACTERS.  THE FIRST LINE OF THE DATA FILE MUST CONTAIN A LINE NUMBER AND THE NUMBER OF ",/,
440& " CASES TO BE READ.  THE DATA IS THEN ENTERED ONE CASE PER LINE IN THE FOLLOWING ORDER: "/
450& " LINE NUMBER, OBSERVED DIRECT LABOR REQUIREMENT (Y), CUMULATIVE PRODUCTION PLOT POINT (X1),",/,
460& " AND PRODUCTION RATE PROXY (X2).  THE PROGRAM USES A FREE FIELD READ FORMAT; THEREFORE,",/,
470& " EACH VARIABLE MUST BE SEPARATED BY AT LEAST ONE SPACE (OR OTHER DELIMITER) BUT NO OTHER",/,
480& " SPECIAL FORMAT IS REQUIRED.  AN EXAMPLE OF A DATA FILE WITH 5 CASES IS PRESENTED BELOW:",//,
490& "      100     5",/,
500& "      101     100      9.5      9.5",/,
510& "      102      90     30       20.5",/,
520& "      103      80     55       25",/,
530& "      104      75     82       27",/,
540& "      105      71    113       31",//,
550& " ONE ADVANTAGE OF THIS PROGRAM IS THAT THE RESULTS OBTAINED WILL BE IN THE SAME UNITS AND",/,
560& " FORM AS THE INPUT DATA.  FOR EXAMPLE, IF YOU ARE WORKING IN DIRECT LABOR HOURS PER MONTH",/,
570& " AND EQUIVALENT UNITS, THE RESULTS WILL BE IN TERMS OF THESE UNITS.  ALSO, IF YOU WISH TO USE",/,
580& " A CUMULATIVE AVERAGE APPROACH, ALL YOU NEED DO IS AGGREGATE THE DATA BASE IN THAT MANNER.",//,
590& "      THE PROGRAM BEGINS BY TRANSFORMING THE INPUT DATA TO COMMON LOGARITHMS.  LOG LINEAR",/,
```

```
 " REGRESSION IS THEN PERFORMED AS FOLLOWS:  Y  REGRESSED ON  X1, Y  REGRESSED ON  X2, AND",/,
 " FINALLY Y  REGRESSED ON BOTH X1 AND X2.  OBSERVED DIRECT LABOR REQUIREMENTS, PREDICTED",/,
 " DIRECT LABOR REQUIREMENTS, AND RESIDUALS ARE PRINTED IN ORIGINAL (UNTRANSFORMED) FORM FOR",/,
 " EACH REGRESSION SITUATION.  IN ADDITION, SUMMARY STATISTICS ARE PRINTED FOR EACH MODEL.  THE",/,
 " SUMMARY STATISTICS INCLUDE TWO COEFFICIENTS OF DETERMINATION R SQUARED LOG AND R SQUARED",/,
 " ACTUAL.  THE R SQUARED LOG REPRESENTS THE GOODNESS OF FIT OF THE MODEL TO THE TRANSFORMED",/,
 " DATA (LOG FORM).  THE R SQUARED ACTUAL, ON THE OTHER HAND, IS COMPUTED USING THE",/,
 " UNTRANSFORMED RESIDUALS, AND IS REPRESENTATIVE OF HOW WELL THE MODEL FITS THE UNTRANSFORMED",/,
 " DATA.  THE DURBIN-WATSON STATISTIC IS CALCULATED FOR  ASSESSMENT  OF AUTOCORRELATION",/,
 " OF THE RESIDUALS.")
6 FORMAT(1H1,1X,//,
 "      SEVERAL OPTIONS ARE AVAILABLE WITHIN THIS PROGRAM AND CAN BE SELECTED BY APPROPRIATE",/,
 " ANSWERS TO THE FOLLOWING QUESTIONS:",//,
 "      1.  DO YOU WANT TO CHECK DATA AS IT IS READ FROM FILE ........ AND CONVERTED TO",/,
 "      LOGARITHMS?",//,
 "      YES - WILL CAUSE THE PRINTING OF A LISTING OF THE RATIONAL INPUT DATA AND THE",/,
 "            ASSOCIATED LOGARITHMIC VALUES.",//,
 "      NO  - SUPPRESSES THIS OPTION.",//,
 "      2. COMPLETE PRINTOUT?",//,
 "      YES - WILL CAUSE OUTPUT TO BE PRINTED IN FULL FORMAT AS DESCRIBED ABOVE.",/,
 "      NO - WILL DELETE THE LISTING OF OBSERVED, PREDICTED, AND RESIDUAL VALUES",/,
 "           BETWEEN TABLES OF SUMMARY STATISTICS.  IT WILL ALSO DELETE LISTING OF",/,
 "           INDIVIDUAL MATRICES FOR THE SHORTRANGE PREDICTIVE ABILITY OPTION(I.E.,",/,
 "           ONLY THE SUMMARY TABLE WILL BE LISTED.",//,
 "      3. DO YOU WANT A COMPARISON OF THE SHORTRANGE PREDICTIVE ABILITY OF THE TWO MODELS?",//,
 "      YES - WILL CAUSE THE PREDICTIVE ABILITY TEST OPTION TO BE ACTIVATED AND THE USER WILL",/,
 "           BE TOLD: 'ENTER PREDICTION RANGE (CASE NUMBERS FOR FIRST AND LAST CASES).'",/,
 "           THE USER SHOULD ENTER THE NUMBER OF THE FIRST CASE TO BE PREDICTED FOLLOWED",/,
 "           BY THE LAST CASE TO BE PREDICTED, SEPARATED BY A COMMA.  THE CASE NUMBERS",/,
 "           MUST BE INTEGER VALUES GREATER THAN OR EQUAL TO 2.  THE PREDICTIVE",/,
 "            ABILITY TEST SIMULATES FUTURE PREDICTIONS BY PERFORMING A STEPWISE TRUNCATION OF",/:
 "            THE HISTORICAL DATA.  FOR THIS REASON, AN UPPER LIMITATION ON THE NUMBER OF",/,
 "            CASES TRUNCATED WOULD BE: ((TOTAL NUMBER OF CASES IN DATA FILE) / 2) - 2",/,
 "            FOR EXAMPLE, IF YOUR DATA FILE CONTAINS 50 CASES, YOUR UPPER LIMIT WOULD BE",/,
 "            23 CASES.  THIS, OF COURSE, REPRESENTS ONLY THE MAXIMUM NUMBER OF CASES THAT",/,
 "            COULD BE TRUNCATED.  IN PRACTICE YOU MAY WANT TO TRUNCATE ONLY A SMALL NUMBER OF",/,
 "            CASES.  THUS, IF YOUR DATA IS COLLECTED IN MONTHLY INTERVALS, YOU CAN LOOK AT",/,
 "            THE PREDICTIVE ABILITY OF THE FULL AND REDUCED MODELS FOR AN 18 MONTH TIME SPAN BY",/,
 "           SPECIFYING AN 18 CASE RANGE.  IF YOUR DATA IS COLLECTED IN QUARTERS, YOU CAN LOOK",/,
 "            AT THE PREDICTIVE ABILITY OF BOTH MODELS FOR AN 18 MONTH TIME SPAN BY SPECIFYING",/,
 "            '6'.  AFTER ALL PREDICTIVE ABILITY TEST SITUATIONS ARE PRINTED, THE PROGRAM",/,
 "            PRINTS A SUMMARY OF THE TEST RESULTS.",//,
 "      NO  - SUPPRESSES THIS OPTION.",//,
 "      4.  DO YOU WANT PROJECTION AND SENSITIVITY MATRIX?",//,
 "      YES - WILL CAUSE PRINTING OF PROJECTION AND SENSITIVITY MATRIX.  THIS MATRIX PRESENTS",/,
 "            PROJECTED DIRECT LABOR REQUIREMENTS FOR SELECTED PAIRS OF CUMULATIVE PRODUCTION",/,
 "            PLOT POINTS AND PRODUCTION RATES.  THE PROJECTION INTERVAL FOR THE CUMULATIVE",/,
 "            PRODUCTION PLOT POINT IS 1% OF THE LAST OBSERVED VALUE.  THE PROJECTION VALUES",/,
 "            FOR PRODUCTION RATE ARE 70, 80, 90, 100, 110, 120, 130, 140, AND 150 PERCENT OF",/,
 "             THE LAST OBSERVED VALUE OF PRODUCTION RATE.",//,
 "       NO  -SUPPRESSES THIS OPTION.",//,
 " ***SPECIAL NOTE***  THE PREDICTED DIRECT LABOR REQUIREMENTS AND RESIDUALS FOR EACH MODEL",/,
```

```
1012& "    ARE STORED IN SEPARATE FILES.  THE VALUES FOR THE STANDARD LEARNING CURVE MODEL ARE",/,
1013& "    STORED IN A FILE CALLED 'STDLEARN'; THE VALUES FOR THE PRODUCTION RATE VARIABLE ALONE",/,
1014& "    MODEL IN THE FILE 'REDHOURS'; AND THE VALUES FOR THE COMBINED CUM. PRODUCTION AND",/,
1015& "    PRODUCTION RATE MODEL IN THE FILE 'FULLMODL'.  USERS MAY ACCESS THESE FILES FOR ",/,
1016& "    RESIDUAL ANALYSIS BY OTHER COPPER IMPACT STATISTICAL PROGRAMS, IF DESIRED.")
1020C
1030C
1040C**************************************************************************************
1050C     DIMENSIONING VARIABLES
1060C**************************************************************************************
1070 ALPHA ANSWER(10),ANS(10)
1080       FILENAME DATAFILE
1090       DIMENSION PLOT(150),RATE(150),HRS(150),Y(150),X1(150),X2(150),LN(150),
1100&      NEWPLOT(150),PRORATE(15),FHRS(150,15),ADEVR(999),ADEVF(999),RESID(200)
1110       DATA SUMHRS,SUMX1,SUMX2,SUMY,SSX1,SSX2,SUMX1Y,SUMX2Y,SUMX1X2,
1120&      SSE,SSE1,SSE2,SSEL,SSEL1,SSEL2,SSTO,SSTO1,SSTO2,SSTOL,SSTOL1,SSTOL2/21*0/
1130C**************************************************************************************
1140C
1150C     PART I - BEGIN PROGRAM, INSTRUCTIONS, DATA INPUT, DATA TRANSFORMATION, AND OPTION SELECTIONS.
1160C
1170C**************************************************************************************
1180 PRINT 1195
1190 1195 FORMAT(1X"                         THE CUMULATIVE PRODUCTION AND PRODUCTION RATE COST MODEL")
1200C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
1210C      INSTRUCTIONS OPTION SELECTION
1220C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
1222 OPTION NOWARN
1230 OPEN(FILE='LOGFILE',UNIT=4,ACCESS='LINENO',STATUS='UNKNOWN')
1240 OPEN(FILE='STDCURVE')
1250 OPEN(FILE='REDCURVE')
1260 OPEN(FILE='FULCURVE')
1270 OPEN(FILE='STDLEARN')
1280 OPEN(FILE='REDHOURS')
1290 OPEN(FILE='FULLMODL')
1300 CLOSE(FILE='STDCURVE')
1310 CLOSE(FILE='REDCURVE')
1320 CLOSE(FILE='FULCURVE')
1340       PRINT 10
1350    10 FORMAT(1H0"DO YOU WANT INSTRUCTIONS")
1360  100  INPUT, ANSWER(1)
1370       IF (ANSWER(1).EQ."NO") GO TO 102
1380       IF (ANSWER(1).EQ."YES") GO TO 101
1390       PRINT," ANSWER YES OR NO ONLY PLEASE"
1400       PRINT," "
1410       GO TO 100
1420 101 PRINT 5
1430 PRINT 6
1440 102 PRINT,"COMPLETE PRINTOUT"
1450 INPUT,ANS(3)
1460 IF(ANS(3).EQ."NO".OR.ANS(3).EQ."YES")GO TO 672
1470 PRINT,"ANSWER YES OR NO ONLY PLEASE"
1480 GO TO 102
```

```
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     INPUT THE DATA AND TRANSFORM THE VARIABLES TO LOGARITHMS
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C
 672 PRINT 20
   20 FORMAT(1X,"PLEASE ENTER THE NAME OF YOUR DATA FILE")
       INPUT, DATAFILE
       READ(DATAFILE,*)LN(1),NCASES
      DO 30 I=1,NCASES
       READ(DATAFILE,*)LN(I),HRS(I),PLOT(I),RATE(I)
       Y(I)  = ALOG10(HRS(I))
       X1(I) = ALOG10(PLOT(I))
       X2(I) = ALOG10(RATE(I))
 WRITE(4,26)I,Y(I),X1(I),X2(I)
 26 FORMAT (1X,I2,2X,F9.7,2X,F9.7,2X,F9.7)
       SUMHRS = SUMHRS + HRS(I)
       SUMX1  = SUMX1  + X1(I)
       SUMX2  = SUMX2  + X2(I)
       SUMY   = SUMY   + Y(I)
       SSX1   = SSX1   + X1(I)**2
       SSX2   = SSX2   + X2(I)**2
       SST    = SST + Y(I)**2
       SUMX1Y = SUMX1Y + X1(I)*Y(I)
       SUMX2Y = SUMX2Y + X2(I)*Y(I)
       SMX1X2 = SMX1X2 + X1(I)*X2(I)
    30CONTINUE
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     DATA CHECK OPTION SELECTION
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
 PRINT 35,DATAFILE
    35 FORMAT(1X,"DO YOU WANT TO CHECK DATA AS IT IS READ FROM FILE ",A8," AND CONVERTED TO LOGARITHMS")
  103  INPUT,ANSWER(2)
       IF (ANSWER(2).EQ."NO") GO TO 104
       IF (ANSWER(2).EQ."YES") GO TO 104
       PRINT," ANSWER YES OR NO ONLY PLEASE"
       GO TO 103
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     PREDICTIVE ABILITY TEST OPTION SELECTION
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
  104  PRINT 40
    40 FORMAT(1X,"DO YOU WANT A COMPARISON OF THE SHORTRANGE PREDICTIVE ABILITY OF THE TWO MODELS")
  105  INPUT,ANSWER(3)
       IF (ANSWER(3).EQ."NO") GO TO 106
       IF (ANSWER(3).EQ."YES") GO TO 203
       PRINT," ANSWER YES OR NO ONLY PLEASE"
       GO TO 105
 203 PRINT 42
    42 FORMAT(1X,"ENTER PREDICTION RANGE (CASE NUMBERS FOR FIRST AND LAST CASES)")
 1900 INPUT,ITRUNC,ITOEUP
 IF(NCASES-ITRUNC+1.LE.NCASES/2-2)GO TO 106
 PRINT 1904
 1904 FORMAT(1H ,'NUMBER OF CASES INPUT EXCEED ALLOWABLE AMOUNT--REENTER NUMBER OF CASES TO BE TRUNCATED')
 GO TO 1900
```

```
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C      PROJECTION AND SENSITIVITY MATRIX OPTION SELECTION
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
  106  PRINT 45
    45 FORMAT(1X,"DO YOU WANT PROJECTION AND SENSITIVITY MATRIX")
  107  INPUT,ANSWER(4)
       IF (ANSWER(4).EQ."NO") GO TO 108
       IF (ANSWER(4).EQ."YES") GO TO 108
       PRINT," ANSWER YES OR NO ONLY PLEASE"
       GO TO 107
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C      BEGIN DATA CHECK OPTION
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
  108  IF (ANSWER(2).EQ."NO") GO TO 109
 PRINT 50,DATAFILE
    50 FORMAT(1H1,//,75("*"),/,5X,"INPUT DATA AS READ FROM FILE ",A8," AND CONVERTED TO LOGARITHMS",
&       /,75("*"))
       PRINT," LINE    DIRECT LABOR HOURS  * CUM PROB PLOT POINT * PRODUCTION RATE"
       PRINT," NUMBER  RATIONAL  LOGARITHM * RATIONAL  LOGARITHM * RATIONAL  LOGARITHM"
       DO 60 I=1,NCASES
       PRINT 55,LN(I),HRS(I),Y(I),PLOT(I),X1(I),RATE(I),X2(I)
    55 FORMAT(1X,1X,I3,5X,F8.2,2X,F9.7," * ",F8.2,2X,F9.7," * ",F8.2,2X,F9.7)
    60CONTINUE
       PRINT 65
    65 FORMAT (1X,75("*"))
 109 CONTINUE
C***********************************************************************************************
C
C      PART II - PEARSON CORRELATION COEFFICIENTS AND REGRESSION ANALYSIS
C
C***********************************************************************************************
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C      CALCULATE AND PRINT PEARSON CORRELATION COEFFICIENTS
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
       RX1Y  = (SUMX1Y-SUMX1*SUMY/NCASES)/SQRT((SSX1-(SUMX1**2/NCASES))*(SSY-(SUMY**2/NCASES)))
       RX2Y  = (SUMX2Y-SUMX2*SUMY/NCASES)/SQRT((SSX2-(SUMX2**2/NCASES))*(SSY-(SUMY**2/NCASES)))
       RX1X2 = (SMX1X2-SUMX1*SUMX2/NCASES)/SQRT((SSX1-(SUMX1**2/NCASES))*(SSX2-(SUMX2**2/NCASES)))
       RX1X1 = 1.0
       RX2X2 = 1.0
       RYY   = 1.0
       PRINT 71,RYY,RX1Y,RX2Y,RX1Y,RX1X1,RX1X2,RX2Y,RX1X2,RX2X2
    71 FORMAT(1X,///,1X,45("*"),/,4X,"PEARSON CORRELATION COEFFICIENTS ",
&      "MATRIX",/,1X,45("*"),//,6X,"*",3X,"Y",6X,"*",5X,"X1",5X,"*",5X,
&      "X2",/,1X,45("*"),/,2X,"Y",3X,3("* ",F10.7,1X),/,1X,45("*"),/,2X,
&      "X1",2X,3("* ",F10.7,1X),/,1X,45("*"),/,2X,"X2",2X,3("* ",F10.7,1X),////)
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C      CALCULATE AND PRINT THE REGRESSION RESULTS OF THE STANDARD LEARNING CURVE MODEL
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
       B1 =(SUMX1Y-((SUMX1*SUMY)/NCASES))/(SSX1-(SUMX1**2/NCASES))
       YBAR = SUMY/NCASES
       HRSBAR = SUMHRS/NCASES
       X1BAR = SUMX1/NCASES
```

```
      X2BAR = SUMX2/NCASES
      B0 = YBAR- B1*X1BAR
      AB0 = 10.**B0
IF(ANS(3).EQ."NO")PRINT 775
775 FORMAT(//1X,75("*"),/14X,"RESULTS OF STANDARD LEARNING CURVE MODEL")
IF(ANS(3).EQ."NO")GO TO 776
PRINT 75
   75 FORMAT(1X,75("*"),/,14X,"RESULTS OF THE STANDARD LEARNING",
&     " CURVE MODEL",/,1X,75("*"),/,1X,"CASE",3X,"OBSERVED",5X,"PREDICTED",
&     5X,"RESIDUAL",5X,"% DEVIATION")
776 DO 110 I=1,NCASES
      YHATL  = B0 + B1 * X1(I)
      RESIDL = Y(I) - YHATL
      SSEL1  = SSEL1 + RESIDL ** 2
      SSTOL1 = SSTOL1 + (Y(I) - YBAR) ** 2
      YHAT   = 10 ** YHATL
      RESID(I) = HRS(I) - YHAT
      PERCENT= (RESID(I)/ HRS(I)) * 100
      SSE1   = SSE1 + RESID(I)** 2
      SST01  = SST01 + (HRS(I) - HRSBAR) ** 2
WRITE("STDLEARN",20)YHAT,RESID(I)
20 FORMAT(F8.2,F8.2)
IF(ANS(3).EQ."NO")GO TO 110
      PRINT 80,I,HRS(I),YHAT,RESID(I),PERCENT
   80 FORMAT(1X,I3,4X,F8.2,6X,F8.2,5X,F8.2,7X,F6.2)
 110 CONTINUE
CLOSE(FILE='STDLEARN')
CALL SYSTEM("/SORT*** STDLEARN;STDCURVE;2R0!-1,-2",$2800)
DO 2770 I=1,NCASES
READ('STDCURVE',*)YHAT,RESID(I)
SUMRESID=SUMRESID+RESID(I)**2
IF(I.GT.1)
RESIDIF=RESID(I)-RESID(I-1)
RESIDIF2=RESIDIF**2
RESIDSUM=RESIDSUM+RESIDIF2
ENDIF
2770 CONTINUE
DWSTAT=RESIDSUM/SUMRESID
SUMRESID=RESIDSUM=0
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     CALCULATE AND PRINT STATISTICS FOR THE STANDARD LEARNING CURVE MODEL
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
2800 NDFD=NCASES-2
      TMSRL = (SSTOL1 - SSEL1)
      TMSEL = SSEL1 / NDFD
      SEE   = SQRT (TMSEL)
      VARB0 = SEE / (1 / NCASES + X1BAR **2 / (SSX1 - (SUMX1 ** 2 / NCASES)))
      SEB0  = SQRT (VARB0)
      SEB1  = SEE / (SQRT(SSX1-(SUMX1**2/NCASES)))
      RSQL1 = (SSTOL1 - SSEL1) / SSTOL1
      RSQA1 = (SST01- SSE1) / SST01
      FRATIO= TMSRL / TMSEL
      PLEARN= (10 ** (B1 * ALOG10(2.0))) * 100
```

```
      PRINT 81,B0,SEB0,A00,B1,SEB1,RSQL1,SEE,THSEL,THSRL,FRATIO,NDFD,RSQA1,PLEARN,DWSTAT
   81 FORMAT(1X,75("*"),/,1X,"THE EQUATION FOR THIS MODEL IS: ",
&     "     THAT = B0 * X1 ** B1",/,1X,
&     "IN LOG FORM THIS MODEL BECOMES: LOG(THAT) = LOG(B0) + B1 * LOG(X1)",
&     /,1X,"WHERE: LOG(B0) =",F8.5,4X,"STD ERROR =",F8.5,4X,"B0 =",F11.5,
&     /,13X,"B1 =",F8.5,4X,"STD ERROR =",F8.5,
&     /,1X,"SUMMARY STATISTICS:",/,1X,
&     "R SQUARED LOG   =",F7.5,10X,"STD ERROR EST =",F11.4,/,1X,
&     "MSE",13X,"=",F9.5,8X,"MSR",11X,"=",F9.5,/,1X,
&     "F RATIO",9X,"=",F9.4,8X,"D. F. (N/D)   = 1/",I3,/1X,
&     "R SQUARED ACTUAL=",F7.5,8X,"LEARNING FACTOR =",F9.5," PERCENT",
& /1X,"DURBIN-WATSON STATISTIC="F9.6
&     /,1X,75("*"))
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     CALCULATE AND PRINT THE REGRESSION RESULTS FOR THE REDUCED HRS VS RATE MODEL
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
      B2 =(SUMX2Y-((SUMX2*SUMY)/NCASES))/(SSX2-(SUMX2**2/NCASES))
      B0 = YBAR - B2 * X2BAR
A00=10**B0
IF(ANS(3).EQ."YES")GO TO 3820
PRINT 820
820 FORMAT(//1X,75("*")/11X,"RESULTS OF REGRESSION ON PRODUCTION RATE VARIABLE ALONE")
GO TO 3860
3820 PRINT 82
   82 FORMAT(1X,75("*"),/,11X,"RESULTS OF REGRESSION ON PRODUCTION",
&     " RATE VARIABLE ALONE",/,1X,75("*"),/,1X,"CASE",3X,"OBSERVED",5X,
&     "PREDICTED",5X,"RESIDUAL",5X,"% DEVIATION")
3860 DO 111 I=1,NCASES
      THATL  = B0 + B2 * X2(I)
      RESIDL = Y(I) - THATL
      SSELZ   = SSEL2 + RESIDL **2
      SSTOL2  = SSTOL2 + (Y(I) - YBAR) ** 2
      THAT   = 10 ** THATL
      RESID(I) = HRS(I) - THAT
      PERCENT= (RESID(I)/ HRS(I)) * 100
      SSE2   = SSE2 + RESID(I)**2
      SST02  = SST02 + (HRS(I) - HRSBAR) ** 2
WRITE("REDHOURS",20)THAT,RESID(I)
IF(ANS(3).EQ."NO")GO TO 111
      PRINT 80,I,HRS(I),THAT,RESID(I),PERCENT
 111 CONTINUE
CLOSE(FILE='REDHOURS')
CALL SYSTEM('/SORT*** REDHOURS;REDCURVE;ZR0;-1,-Z',&3340)
DO 3314 I=1,NCASES
READ('REDCURVE',*)THAT,RESID(I)
SUMRESID=SUMRESID+RESID(I)**2
IF(I.GT.1)
RESIDIF=RESID(I)-RESID(I-1)
RESIDIF2=RESIDIF**2
RESIDSUM=RESIDSUM+RESIDIF2
ENDIF
3314 CONTINUE
```

```
DWSTAT=RESIDSUM/SUMRESID
SUMRESID=RESIDSUM=0
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     CALCULATE AND PRINT STATISTICS FOR THE REDUCED HRS VS RATE MODEL
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
3340 TMSRL=(SSTOL2-SSEL2)
      TMSEL = SSEL2 / NDFD
      SEE   = SQRT(TMSEL)
      VARB0 = SEE / (1 / NCASES + X2BAR ** 2 / (SSX2 - (SUMX2 ** 2 / NCASES)))
      SEB0  = SQRT (VARB0)
      SEB2  = SEE / (SQRT (SSX2 - (SUMX2 ** 2 / NCASES)))
      RSQL2 = (SSTOL2 - SSEL2) / SSTOL2
      RSQA2 = (SST02- SSE2) / SST02
      FRATIO= TMSRL / TMSEL
      PRINT 83,B0,SEB0,AB0,B2,SEB2,RSQL2,SEE,TMSEL,TMSRL,FRATIO,NDFD,RSQA2,DWSTAT
83 FORMAT(1X75("*")/1X"THE EQUATION FOR THIS MODEL IS: "
&     "     YHAT = B0 * X2 ** B2",/,1X
&     "IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B2 * LOG(X2)",
&     /,1X,"WHERE: LOG(B0) =",F8.5,4X,"STD ERROR =",F8.5,4X,"B0 =",F11.5,
&     /,13X,"B2 =",F8.5,4X,"STD ERROR =",F8.5,
&     /,1X,"SUMMARY STATISTICS:",/,1X,
&     "R SQUARED LOG   =",F7.5,10X,"STD ERROR EST =",F11.4,/,1X,
&     "MSE",13X,"=",F9.5,8X,"MSR",11X,"=",F9.5,/,1X,
&     "F RATIO",9X,"=",F9.4,8X,"D. F. (N/D)   = 1/",I3,/,1X,
& "R SQUARED ACTUAL="F7.5/1X"DURBIN-WATSON STATISTIC="F9.6/1X75("*"))
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     CALCULATE AND PRINT THE REGRESSION RESULTS FOR THE FULL MODEL
C:::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
      DENOM = ((SSX1-X1BAR*SUMX1)*(SSX2-X2BAR*SUMX2) - (SMX1X2-X1BAR*SUMX2)**2)
      B1 =((SSX2-X2BAR*SUMX2)*(SUMX1Y-X1BAR*SUMY) -
&         (SMX1X2-X1BAR*SUMX2)*(SUMX2Y-X2BAR*SUMY))/DENOM
      B2 = ((SSX1-X1BAR*SUMX1) *(SUMX2Y-X2BAR*SUMY) -
&        (SMX1X2-X1BAR*SUMX2)*(SUMX1Y-X1BAR*SUMY))/DENOM
      B0 = YBAR-B1*X1BAR-B2*X2BAR
      AB0 = 10.**B0
IF(ANS(3).EQ."YES")GO TO 4320
PRINT 840
840 FORMAT(//1X,75("*")/6X,"RESULTS OF COMBINED CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL")
GO TO 4360
4320 PRINT 84
   84 FORMAT(1X,75("*"),/,6X,"RESULTS OF COMBINED CUMULATIVE PRODUCTION",
&     " AND PRODUCTION RATE MODEL",/,1X,75("*"),/,1X,"CASE",3X,"OBSERVED",5X,
&     "PREDICTED",5X,"RESIDUAL",5X,"% DEVIATION")
4340 DO 112 I=1,NCASES
      YHATL = B0 + B1 * X1(I) + B2 * X2(I)
      RESIDL= Y(I) - YHATL
      SSEL  = SSEL + RESIDL ** 2
      SSTOL = SSTOL + (Y(I) - YBAR) ** 2
      YHAT  = 10 ** YHATL
      RESID(I)= HRS(I) - YHAT
      PERCENT= (RESID(I)/ HRS(I)) * 100
      SSE   = SSE + RESID(I)** 2
```

```
      SSTO  = SSTO + (HRS(I) - HRSBAR) ** 2
WRITE("FULLMODL",20)THAT,RESID(I)
IF(ANS(3).EQ."NO")GO TO 112
      PRINT 80,I,HRS(I),THAT,RESID(I),PERCENT
 112 CONTINUE
CLOSE(FILE='FULLMODL')
CALL SYSTEM('/SORT*** FULLMODL;FULCURVE;2R0;-1,-2',&3890)
DO 3864 I=1,NCASES
READ('FULCURVE',*)THAT,RESID(I)
SUMRESID=SUMRESID+RESID(I)**2
IF(I.GT.1)
RESIDIF=RESID(I)-RESID(I-1)
RESIDIF2=RESIDIF**2
RESIDSUM=RESIDSUM+RESIDIF2
ENDIF
3864 CONTINUE
DWSTAT=RESIDSUM/SUMRESID
SUMRESID=RESIDSUM=0
C     CALCULATE AND PRINT STATISTICS FOR THE FULL MODEL
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
3890 NDFD=NCASES-3
      THSRL = (SSTOL - SSEL) / 2
      THSEL = SSEL / NDFD
      SEE   = SQRT(THSEL)
      ZVAL  = NCASES*(SSX1 * SSX2 - SMX1X2 ** 2) - SUMX1*(SUMX1 * SSX2 -
&             SMX1X2 * SUMX2) + SUMX2*(SUMX1 * SMX1X2 - SSX1 * SUMX2)
      AVAL  = (SSX1 * SSX2 - SMX1X2 ** 2) / ZVAL
      VARB0 = THSEL * AVAL
      SEB0  = SQRT (VARB0)
      SEB1  = SQRT((THSEL * (SSX2 - X2BAR * SUMX2)) / DENOM)
      SEB2  = SQRT((THSEL * (SSX1 - X1BAR * SUMX1)) / DENOM)
      RSQL  = (SSTOL - SSEL) / SSTOL
      RSQA  = (SSTO - SSE) / SSTO
      FRATIO= THSRL /THSEL
      FB1   = (RSQL - RSQL2) / ((1 - RSQL) / (NCASES - 3))
      FB2   = (RSQL - RSQL1) / ((1 - RSQL) / (NCASES - 3))
      PRINT 85,B0,SEB0,AB0,B1,SEB1,FB1,B2,SEB2,FB2,RSQL,SEE,THSEL,THSRL,FRATIO,NDFD,RSQA,DWSTAT
   85 FORMAT(1X,75("*"),/,1X,"THE EQUATION FOR THIS MODEL IS: ",
&     "     THAT = B0 * X1 ** B1 * X2 **B2",/,1X,
&     "IN LOG FORM THIS MODEL BECOMES: LOG(THAT) = LOG(B0) + B1 * LOG(X1) + B2 * LOG(X2)",
&     /,1X,"WHERE: LOG(B0) =",F8.5,4X,"STD ERROR =",F8.5,4X,"B0 =",F11.5,
&     /,13X,"B1 =",F8.5,4X,"STD ERROR =",F8.5,4X,"F* =",F10.4,/,
&     13X,"B2 =",F8.5,4X,"STD ERROR =",F8.5,4X,"F* =",F10.4,/,1X,
&     "SUMMARY STATISTICS:",/,1X,"R SQUARED LOG   =",F7.5,10X,
&     "STD ERROR EST =",F11.4,/,1X,"MSE",13X,"=",F9.5,8X,"MSR",11X,"=",F9.5,/,1X,
&     "F RATIO",9X,"=",F9.4,8X,"D. F. (N/D)    = 2/",I3,/,1X,
& "R SQUARED ACTUAL="F7.5/1X"DURBIN-WATSON STATISTIC="F9.6/1X75("*"))
C*********************************************************************************
C
C     PART III - PREDICTIVE ABILITY TEST OPTION
C
C*********************************************************************************
```

```
      IF (ANSWER(3).EQ."NO") GO TO 116
IF(ANS(3).EQ."NO")PRINT 4173
ITRUNC=NCASES-ITRUNC+1
ITOEUP=NCASES-ITOEUP+1
DO 113 I=ITOEUP,ITRUNC
      ITEST = NCASES + 1 - I
4173 FORMAT(//)
IF(ANS(3).EQ."NO")GO TO 4900
      PRINT 86,ITEST,HRS(ITEST)
   86 FORMAT(1X,116("*"),/,1X,"*",37X,"SHORTRANGE PREDICTIVE ABILITY ",
&     "COMPARISON",37X,"*",/,1X,"*",16X,
&     "THE DATA PRESENTED BELOW IS FOR CASE #",I3," WHICH HAS AN OBSERVED",
&     " VALUE OF:",F9.2,16X,"*",/,
&     1X,116("*"),/1X,"*",3X,"#",3X,"*",9X,"REDUCED (LEARNING CURVE) ",
&     "MODEL",8X,"**",3X,"FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) ",
&     "MODEL",2X,"*",/,1X,"*"," CASES ",100("*"),/,1X,"*  USED * ",
&     "PREDICTION * % DEVIATION *  EST B0  * EST B1  ** ",
&     "PREDICTION * % DEVIATION *  EST B0  * EST B1  * EST B2  *",
&     /,1X,116("*"))
4900 DO 114 J=1,ITRUNC
      ICASES = ITEST - J
      SUMY   =-0
      SUMX1  = 0
      SUMX2  = 0
      SSX1   = 0
      SSX2   = 0
      SUMX1Y = 0
      SUMX2Y = 0
      SMX1X2 = 0
     DO 115 K=1,ICASES
      SUMY   = SUMY + Y(K)
      SUMX1  = SUMX1 + X1(K)
      SUMX2  = SUMX2 + X2(K)
      SSX1   = SSX1 + X1(K) ** 2
      SSX2   = SSX2 + X2(K) ** 2
      SUMX1Y = SUMX1Y + X1(K) * Y(K)
      SUMX2Y = SUMX2Y + X2(K) * Y(K)
      SMX1X2 = SMX1X2 + X1(K) * X2(K)
 115 CONTINUE
      ICOUNTA = ICOUNTA + 1
      YBAR  = SUMY / ICASES
      X1BAR = SUMX1 / ICASES
      X2BAR = SUMX2 / ICASES
      B1R   = (SUMX1Y - ((SUMX1 * SUMY) / ICASES)) / (SSX1 - (SUMX1 ** 2 / ICASES))
      B0R   = YBAR - B1R * X1BAR
      AB0R  = 10 ** B0R
      YHATR = 10 ** (B0R + B1R * X1(ITEST))
      DEVR    = HRS(ITEST) - YHATR
      ABDEVR(ICOUNTA) = ABS(DEVR)
      SUMABDEVR = SUMABDEVR + ABDEVR(ICOUNTA)
      PDEVR   = 100 * DEVR/HRS(ITEST)
      APDEVR = ABS(PDEVR)
```

```
      IF (APDEVR.GT.10.0) GO TO 201
      ICOUNTCR = ICOUNTCR + 1
      IF (APDEVR.GT.5.0) GO TO 201
      ICOUNTER = ICOUNTER + 1
 201  DENOM = ((SSI1-I1BAR*SUMI1)*(SSI2-I2BAR*SUMI2) - (SMI1I2-I1BAR*SUMI2)**2)
      B1F   = ((SSI2-I2BAR*SUMI2)*(SUMI1Y-I1BAR*SUMY) -
&            (SMI1I2-I1BAR*SUMI2)*(SUMI2Y-I2BAR*SUMY))/DENOM
      B2F   = ((SSI1-I1BAR*SUMI1)*(SUMI2Y-I2BAR*SUMY) -
&            (SMI1I2-I1BAR*SUMI2)*(SUMI1Y-I1BAR*SUMY))/DENOM
      B0F   = YBAR - B1F * I1BAR - B2F * I2BAR
      AB0F  = 10 ** B0F
      YHATF = 10  ** (B0F + B1F * I1(ITEST) + B2F * I2(ITEST))
      DEVF  = HRS(ITEST) - YHATF
      ADEVF(ICOUNTA) = ABS(DEVF)
      SUMADEVF = SUMADEVF + ADEVF(ICOUNTA)
      PDEVF = 100 * DEVF/HRS(ITEST)
      APDEVF = ABS(PDEVF)
      IF (APDEVF.GT.10.0) GO TO 202
      ICOUNTCF = ICOUNTCF + 1
      IF (APDEVF.GT.5.0) GO TO 202
      ICOUNTEF = ICOUNTEF + 1
 202 IF(ANS(3).EQ."NO")GO TO 114
    PRINT 87,ICASES,YHATR,PDEVR,AB0R,B1R,YHATF,PDEVF,AB0F,B1F,B2F
    87 FORMAT(1X,"*",2X,I3,2X,"*",1X,F9.2,2X,"*",3X,F6.2,4X,"*",F9.2,1X,
&      "*",F8.5,1X,"**",1X,F9.2,2X,"*",3X,F6.2,4X,"*",F9.2,1X,"*",F8.5,1X,
&      "*",F8.5,1X,"*")
  114 CONTINUE
 IF(ANS(3).EQ."NO")GO TO 5590
      PRINT 88
    88 FORMAT(1X,116("*"),//////)
 5590 COUNT=COUNT+1.
      FLAG1 = COUNT / 2.0
      FLAG2 = FLAG1 - INT(FLAG1)
      IF (FLAG2.NE.0.0) GO TO 113
  113 CONTINUE
      AVCADEVR = SUMADEVR / ICOUNTA
      AVCADEVF = SUMADEVF / ICOUNTA
     DO 119 I =1,ICOUNTA
      SSDEVR  = SSDEVR + (ADEVR(I) - AVCADEVR)**2
      SSDEVF  = SSDEVF + (ADEVF(I) - AVCADEVF)**2
  119 CONTINUE
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C     CALCULATE AND PRINT RESULTS SUMMARY FOR PREDICTIVE ABILITY TESTS
C::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
      VARADEVR = SSDEVR / (ICOUNTA - 1)
      VARADEVF = SSDEVF / (ICOUNTA - 1)
      TESTSTAT = (AVCADEVR-AVCADEVF)/SQRT((VARADEVR/ICOUNTA)+(VARADEVF/ICOUNTA))
      PCENTER = 100 * ICOUNTER / ICOUNTA
      PCENTCR = 100 * ICOUNTCR / ICOUNTA
      PCENTEF = 100 * ICOUNTEF / ICOUNTA
      PCENTCF = 100 * ICOUNTCF / ICOUNTA
      PRINT 95,AVCADEVR,AVCADEVF,VARADEVR,VARADEVF,TESTSTAT,ICOUNTA,
```

```
&      ICOUNTA,ICOUNTER,ICOUNTEF,PCENTER,PCENTEF,ICOUNTGR,ICOUNTGF,PCENTGR,
&      PCENTGF
    95 FORMAT(1X,67("*"),/,1X,"*",10X,"SUMMARY OF PREDICTIVE ABILITY TESTS",
&      " RESULTS",12X,"*",/,1X,67("*"),/,1X,"*",9X,"ITEMS OF INTEREST",8X,
&      "* REDUCED MODEL *  FULL MODEL  *",/,1X,67("*"),/,1X,"* AVERAGE ",
&      "ABSOLUTE DEVIATION",7X,"*",3X,F9.2,3X,"*",2X,F9.2,3X,"*",/,1X,
&      "* VARIANCE OF ABSOLUTE DEVIATIONS",2X,"*",1X,F11.2,3X,"*",F11.2,3X,
&      "*",/,1X,"* TEST STATISTIC (SEE NOTE)",8X,"*",6X,"---",6X,"*",2X,
&      F9.2,3X,"*",/,1X,"* TOTAL NUMBER OF TEST SITUATIONS  *",6X,I3,6X,"*",
&      5X,I3,6X,"*",/,1X,"* NUMBER OF PREDICTIONS WITHIN 5%  *",6X,I3,6X,
&      "*",5X,I3,6X,"*",/,1X,"* PERCENT OF PREDICTIONS WITHIN 5% *",6X,F4.0,
&      5X,"*",5X,F4.0,5X,"*",/,1X,"* NUMBER OF PREDICTIONS WITHIN 10% *",
&      6X,I3,6X,"*",5X,I3,6X,"*",/,1X,"* PERCENT OF PREDICTIONS WITHIN 10%*",
&      6X,F4.0,5X,"*",5X,F4.0,5X,"*",/,1X,67("*"),/,1X,"NOTE: IN TESTING FOR ",
&      "STATISTICAL SIGNIFICANCE USE STUDENT'S T DISTRIBUTION",/,1X
&      "IF THE NUMBER OF TEST SITUATIONS ARE LESS THAN 60; OTHERWISE ",
&      "USE STANDARD",/,1X,"NORMAL DISTRIBUTION.  IN EITHER CASE THIS IS ",
&      "A ONE TAILED TEST.  IF",/,1X,"THE TEST STATISTIC IS GREATER THAN ",
&      "THE CRITICAL STATISTIC ONE MAY",/,1X,"CONCLUDE THAT THE AVERAGE ",
&      "ABSOLUTE DEVIATION OBTAINED WITH THE FULL",/,1X,"MODEL IS ",
&      "SIGNIFICANTLY LESS THAN THAT OBTAINED WITH THE REDUCED MODEL.")
 PRINT,"FILES LOGFILE,STDLEARN,REDHOURS,AND FULLMODL WRITTEN."
C*****************************************************************************************
C
C     PART IV - PROJECTION AND SENSITIVITY MATRIX OPTION
C
C*****************************************************************************************
  116  IF (ANSWER(4).EQ."NO") GO TO 125
       ADDPLOT = PLOT(NCASES)
      DO 117 I=1,100
       ADDPLOT = ADDPLOT + .01 * PLOT(NCASES)
       NEWPLOT(I) = INT(ADDPLOT)
       ADDRATE = .60 * RATE(NCASES)
      DO 118 J=1,9
       ADDRATE = ADDRATE + .1 * RATE(NCASES)
       PRORATE(J) = ADDRATE
       FHRS(I,J)  = A00 * NEWPLOT(I)**B1 * PRORATE(J)**B2
  118 CONTINUE
  117 CONTINUE
       ISTART = 1
       ISTOP  = 50
      DO 120 K=1,2
       PRINT 89,(PRORATE(J),J=1,9)
    89 FORMAT(1X,113("*"),/,1X,"*",39X,"PROJECTION AND SENSITIVITY MATRIX",
&      39X,"*",/,1X,113("*"),/,1X,"*  PROJECTED *",36X,"PROJECTED PRODUCTION",
&      " RATES",36X,"*",/,1X,"* CUMULATIVE *",99("*"),/,1X,"*    UNITS   *",
&      9(F8.2,2X,"*"),/,1X,113("*"))
      DO 121 I=ISTART,ISTOP
       PRINT 90,NEWPLOT(I),(FHRS(I,J),J=1,9)
    90 FORMAT(1X,"*",3X,I6,3X,"*",9(1X,F8.1,1X,"*"))
  121 CONTINUE
       PRINT 91
```

```
   91 FORMAT(1X,113("*"))
      PRINT92
   92 FORMAT(1X,"NOTE: 1.  PROJECTED VALUES FOR DIRECT LABOR HOURS MAY ",
      "BE READ FROM THE ABOVE MATRIX BY MATCHING A GIVEN PRODUCTION",/,1X,
      "RATE WITH A GIVEN NUMBER OF CUMULATIVE UNITS AND READING THE ",
      "VALUE FOR DIRECT LABOR HOURS FOUND AT THE INTERSECTION",/,1X,
      "OF THE CORESPONDING ROW AND COLUMN.  FORECASTING MODEL IS THE ",
      "CUMULATIVE PRODUCTION & PRODUCTION RATE MODEL.",/,7X,"2.  PROJECT",
      "ION INTERVAL FOR CUMULATIVE UNITS IS 1% OF THE LAST OBSERVED VALUE",
      " OF CUMULATIVE UNITS.",/,7X,"3.  PROJECTION VALUES FOR PRODUCTION ",
      "RATE ARE 70, 80, 90, 100, 110, 120, 130, 140, AND 150 PERCENT OF ",
      "THE",/,1X,"LAST OBSERVED VALUE OF PRODUCTION RATE.")
      ISTART = 51
      ISTOP  = 100
  120 CONTINUE
  125 STOP1
      END
```

Sample PRODRATE Output

This next section provides a sample output of the abbreviated and full format options using simulated data. The data base was developed by Stevens and Thomerson (16:127) to demonstrate how the PRODRATE program works. It should be noted the data were developed to demonstrate superior results for the full model. The program instructions are presented first, then the abbreviated format followed by the full format. This comparison of the optional formats will, hopefully, demonstrate the value of the abbreviated option.

****

PRODRATE INSTRUCTIONS

****

THIS PROGRAM IS DESIGNED TO EVALUATE THE VARIATION IN DIRECT LABOR REQUIREMENTS AS A FUNCTION OF CUMULATIVE PRODUCTION AND PRODUCTION RATE. IN ADDITION, THE ANALYST MAY COMPARE THE RESULTS OBTAINED FROM THE STANDARD LEARNING CURVE WITH THE RESULTS OBTAINED FROM THE CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL. THE COST MODELS USED IN THIS PROGRAM ARE:

1. REDUCED MODEL [STANDARD LEARNING CURVE MODEL]

   Y = B0 * (X1 ** B1) * (10 ** E)

2. FULL MODEL [CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL]

   Y = B0 * (X1 ** B1) * (X2 ** B2) * (10 ** E)

WHERE:	Y	IS THE DIRECT LABOR REQUIREMENTS
	X1	IS THE CUMULATIVE PRODUCTION PLOT POINT
	X2	IS THE PRODUCTION RATE PROXY(E.G. EQUIVALENT UNITS PER MONTH)
	E	REPRESENTS THE ERROR TERM
	B0, B1, AND B2	ARE PARAMETERS DETERMINED BY RECRESSION

DATA ARE INPUT BY READING FROM ANY PROPERLY FORMATTED DATA FILE. YOUR DATA FILE SHOULD BE SAVED TO ANY PERMANENT FILENAME. YOU WILL BE ASK TO INPUT THE NAME OF YOUR DATA FILE AT THE APPROPRIATE STEP IN THE PROGRAM. THE NAME OF YOUR DATA FILE CAN NOT EXCEED 8 CHARACTERS. THE FIRST LINE OF THE DATA FILE MUST CONTAIN A LINE NUMBER AND THE NUMBER OF CASES TO BE READ. THE DATA IS THEN ENTERED ONE CASE PER LINE IN THE FOLLOWING ORDER: LINE NUMBER, OBSERVED DIRECT LABOR REQUIREMENT (Y), CUMULATIVE PRODUCTION PLOT POINT (X1), AND PRODUCTION RATE PROXY (X2). THE PROGRAM USES A FREE FIELD READ FORMAT; THEREFORE, EACH VARIABLE MUST BE SEPARATED BY AT LEAST ONE SPACE (OR OTHER DELIMITER) BUT NO OTHER SPECIAL FORMAT IS REQUIRED. AN EXAMPLE OF A DATA FILE WITH 5 CASES IS PRESENTED BELOW:

```
100   5
101   100    9.5    9.5
102    90    30    20.5
103    80    55    25
104    75    82    27
105    71   113    31
```

ONE ADVANTAGE OF THIS PROGRAM IS THAT THE RESULTS OBTAINED WILL BE IN THE SAME UNITS AND FORM AS THE INPUT DATA. FOR EXAMPLE, IF YOU ARE WORKING IN DIRECT LABOR HOURS PER MONTH AND EQUIVALENT UNITS, THE RESULTS WILL BE IN TERMS OF THESE UNITS. ALSO, IF YOU WISH TO USE A CUMULATIVE AVERAGE APPROACH, ALL YOU NEED DO IS ACCRECATE THE DATA BASE IN THAT MANNER.

THE PROGRAM BEGINS BY TRANSFORMING THE INPUT DATA TO COMMON LOGARITHMS. LOG LINEAR REGRESSION IS THEN PERFORMED AS FOLLOWS: Y REGRESSED ON X1, Y REGRESSED ON X2, AND FINALLY Y REGRESSED ON BOTH X1 AND X2. OBSERVED DIRECT LABOR REQUIREMENTS, PREDICTED DIRECT LABOR REQUIREMENTS, AND RESIDUALS ARE PRINTED IN ORIGINAL (UNTRANSFORMED) FORM FOR EACH REGRESSION SITUATION. IN ADDITION, SUMMARY STATISTICS ARE PRINTED FOR EACH MODEL. THE SUMMARY STATISTICS INCLUDE TWO COEFFICIENTS OF DETERMINATION R SQUARED LOG AND R SQUARED ACTUAL. THE R SQUARED LOG REPRESENTS THE GOODNESS OF FIT OF THE MODEL TO THE TRANSFORMED DATA (LOG FORM). THE R SQUARED ACTUAL, ON THE OTHER HAND, IS COMPUTED USING THE UNTRANSFORMED RESIDUALS, AND IS REPRESENTATIVE OF HOW WELL THE MODEL FITS THE UNTRANSFORMED DATA. THE DURBIN-WATSON STATISTIC IS CALCULATED FOR ASSESSMENT OF AUTOCORRELATION OF THE RESIDUALS.

SEVERAL OPTIONS ARE AVAILABLE WITHIN THIS PROGRAM AND CAN BE SELECTED BY APPROPRIATE ANSWERS TO THE FOLLOWING QUESTIONS:

1. DO YOU WANT TO CHECK DATA AS IT IS READ FROM FILE .... AND CONVERTED TO LOGARITHMS?

YES - WILL CAUSE THE PRINTING OF A LISTING OF THE RATIONAL INPUT DATA AND THE ASSOCIATED LOGARITHMIC VALUES.

NO - SUPPRESSES THIS OPTION.

2. COMPLETE PRINTOUT?

YES - WILL CAUSE OUTPUT TO BE PRINTED IN FULL FORMAT AS DESCRIBED ABOVE.
NO - WILL DELETE THE LISTING OF OBSERVED, PREDICTED, AND RESIDUAL VALUES BETWEEN TABLES OF SUMMARY STATISTICS. IT WILL ALSO DELETE LISTING OF INDIVIDUAL MATRICES FOR THE SHORTRANGE PREDICTIVE ABILITY OPTION;I.E., ONLY THE SUMMARY TABLE WILL BE LISTED.

3. DO YOU WANT A COMPARISON OF THE SHORTRANGE PREDICTIVE ABILITY OF THE TWO MODELS?

YES - WILL CAUSE THE PREDICTIVE ABILITY TEST OPTION TO BE ACTIVATED AND THE USER WILL BE TOLD: 'ENTER PREDICTION RANGE (CASE NUMBERS FOR FIRST AND LAST CASES).' THE USER SHOULD ENTER THE NUMBER OF THE FIRST CASE TO BE PREDICTED FOLLOWED BY THE LAST CASE TO BE PREDICTED, SEPARATED BY A COMMA. THE CASE NUMBERS MUST BE INTEGER VALUES GREATER THAN OR EQUAL TO 2. THE PREDICTIVE ABILITY TEST SIMULATES FUTURE PREDICTIONS BY PERFORMING A STEPWISE TRUNCATION OF THE HISTORICAL DATA. FOR THIS REASON, AN UPPER LIMITATION ON THE NUMBER OF CASES TRUNCATED WOULD BE: ((TOTAL NUMBER OF CASES IN DATA FILE) / 2) - 2 FOR EXAMPLE, IF YOUR DATA FILE CONTAINS 50 CASES, YOUR UPPER LIMIT WOULD BE 23 CASES. THIS, OF COURSE, REPRESENTS ONLY THE MAXIMUM NUMBER OF CASES THAT COULD BE TRUNCATED. IN PRACTICE YOU MAY WANT TO TRUNCATE ONLY A SMALL NUMBER OF CASES. THUS, IF YOUR DATA IS COLLECTED IN MONTHLY INTERVALS, YOU CAN LOOK AT THE PREDICTIVE ABILITY OF THE FULL AND REDUCED MODELS FOR AN 18 MONTH TIME SPAN BY SPECIFYING AN 18 CASE RANGE. IF YOUR DATA IS COLLECTED IN QUARTERS, YOU CAN LOOK AT THE PREDICTIVE ABILITY OF BOTH MODELS FOR AN 18 MONTH TIME SPAN BY SPECIFYING '6'. AFTER ALL PREDICTIVE ABILITY TEST SITUATIONS ARE PRINTED, THE PROGRAM PRINTS A SUMMARY OF THE TEST RESULTS.

NO - SUPPRESSES THIS OPTION.

4. DO YOU WANT PROJECTION AND SENSITIVITY MATRIX?

YES - WILL CAUSE PRINTING OF PROJECTION AND SENSITIVITY MATRIX. THIS MATRIX PRESENTS PROJECTED DIRECT LABOR REQUIREMENTS FOR SELECTED PAIRS OF CUMULATIVE PRODUCTION PLOT POINTS AND PRODUCTION RATES. THE PROJECTION INTERVAL FOR THE CUMULATIVE PRODUCTION PLOT POINT IS 1% OF THE LAST OBSERVED VALUE. THE PROJECTION VALUES FOR PRODUCTION RATE ARE 70, 80, 90, 100, 110, 120, 130, 140, AND 150 PERCENT OF THE LAST OBSERVED VALUE OF PRODUCTION RATE.

NO -SUPPRESSES THIS OPTION.

SPECIAL NOTE THE PREDICTED DIRECT LABOR REQUIREMENTS AND RESIDUALS FOR EACH MODEL ARE STORED IN SEPARATE FILES. THE VALUES FOR THE STANDARD LEARNING CURVE MODEL ARE STORED IN A FILE CALLED 'STDLEARN'; THE VALUES FOR THE PRODUCTION RATE VARIABLE ALONE MODEL IN THE FILE 'REDHOURS'; AND THE VALUES FOR THE COMBINED CUM. PRODUCTION AND PRODUCTION RATE MODEL IN THE FILE 'FULLMODL'. USERS MAY ACCESS THESE FILES FOR RESIDUAL ANALYSIS BY OTHER COPPER IMPACT STATISTICAL PROGRAMS, IF DESIRED.

```
*****************************************************
  PEARSON CORRELATION COEFFICIENTS MATRIX
*****************************************************

    *     Y      *     X1      *     X2
*****************************************************
 Y  *  1.0000000 * -0.9955710 * -0.9841432
*****************************************************
 X1 * -0.9955710 *  1.0000000 *  0.9964648
*****************************************************
 X2 * -0.9841432 *  0.9964648 *  1.0000000
```

```
*************************************************************************
            RESULTS OF STANDARD LEARNING CURVE MODEL
*************************************************************************
THE EQUATION FOR THIS MODEL IS:      YHAT = B0 * X1 ** B1
IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B1 * LOG(X1)
WHERE: LOG(B0) = 3.49572    STD ERROR = 0.13455    B0 = 3131.24004
            B1 =-0.28262    STD ERROR = 0.00433
SUMMARY STATISTICS:
R SQUARED LOG   =0.99115          STD ERROR EST =     0.0164
MSE             =  0.00027        MSR           =  1.14390
F RATIO         =4255.4005        D. F. (N/D)   = 1/ 38
R SQUARED ACTUAL=0.98881        LEARNING FACTOR = 82.20945 PERCENT
DURBIN-WATSON STATISTIC= 0.327753
*************************************************************************
```

```
*************************************************************************
        RESULTS OF REGRESSION ON PRODUCTION RATE VARIABLE ALONE
*************************************************************************
THE EQUATION FOR THIS MODEL IS: "    YHAT = B0 * X2 ** B2
IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B2 * LOG(X2)
WHERE: LOG(B0) = 3.25379    STD ERROR = 0.23957    B0 = 1793.86990
            B2 =-0.74392    STD ERROR = 0.02175
SUMMARY STATISTICS:
R SQUARED LOG   =0.96854          STD ERROR EST =     0.0309
MSE             =  0.00096        MSR           =  1.11780
F RATIO         =1169.7950        D. F. (N/D)   = 1/ 38
R SQUARED ACTUAL=0.95679
DURBIN-WATSON STATISTIC= 0.277285
*************************************************************************
```

```
************************************************************************
     RESULTS OF COMBINED CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL
************************************************************************
THE EQUATION FOR THIS MODEL IS:       YHAT = B0 * X1 ** B1 * X2 **B2
IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B1 * LOG(X1) + B2 * LOG(X2)
WHERE: LOG(B0) = 3.75389    STD ERROR = 0.00116    B0 = 5672.04468
           B1 =-0.59957    STD ERROR = 0.00134    F* =00532.2109
           B2 = 0.04696    STD ERROR = 0.00354    F* =56304.9604
SUMMARY STATISTICS:
R SQUARED LOG   =0.99999          STD ERROR EST =     0.0004
MSE             =  0.00000        MSR           =  0.57705
F RATIO         =7900.2012        D. F. (N/D)   = 2/ 37
R SQUARED ACTUAL=1.00000
DURBIN-WATSON STATISTIC= 2.300320
************************************************************************
```

```
****************************************************************
*          SUMMARY OF PREDICTIVE ABILITY TESTS RESULTS          *
****************************************************************
```

ITEMS OF INTEREST	REDUCED MODEL	FULL MODEL
AVERAGE ABSOLUTE DEVIATION	3.84	0.16
VARIANCE OF ABSOLUTE DEVIATIONS	10.60	0.01
TEST STATISTIC (SEE NOTE)	---	13.50
TOTAL NUMBER OF TEST SITUATIONS	144	144
NUMBER OF PREDICTIONS WITHIN 5%	138	144
PERCENT OF PREDICTIONS WITHIN 5%	95.	100.
NUMBER OF PREDICTIONS WITHIN 10%	144	144
PERCENT OF PREDICTIONS WITHIN 10%	100.	100.

NOTE: IN TESTING FOR STATISTICAL SIGNIFICANCE USE STUDENT'S T DISTRIBUTION IF THE NUMBER OF TEST SITUATIONS ARE LESS THAN 60; OTHERWISE USE STANDARD NORMAL DISTRIBUTION. IN EITHER CASE THIS IS A ONE TAILED TEST. IF THE TEST STATISTIC IS GREATER THAN THE CRITICAL STATISTIC ONE MAY CONCLUDE THAT THE AVERAGE ABSOLUTE DEVIATION OBTAINED WITH THE FULL MODEL IS SIGNIFICANTLY LESS THAN THAT OBTAINED WITH THE REDUCED MODEL.
FILES LOGFILE,STDLEARN,REDHOURS,AND FULLMODL WRITTEN.

INPUT DATA AS READ FROM FILE TESTDATA AND CONVERTED TO LOGARITHMS

LINE NUMBER	DIRECT LABOR HOURS RATIONAL	DIRECT LABOR HOURS LOGARITHM	CUM PROD PLOT POINT RATIONAL	CUM PROD PLOT POINT LOGARITHM	PRODUCTION RATE RATIONAL	PRODUCTION RATE LOGARITHM
100	1088.00	3.0366289	50.00	1.6989700	2.27	0.3560259
110	803.00	2.9047155	175.00	2.2430380	3.85	0.5854607
120	641.00	2.8068580	313.00	2.4955443	4.45	0.6483600
130	560.00	2.7481880	454.00	2.6570559	4.94	0.6937269
140	493.00	2.6928469	626.00	2.7965743	5.33	0.7267272
150	462.00	2.6646420	795.00	2.9003671	5.85	0.7671559
160	437.00	2.6404814	1005.00	3.0021661	6.47	0.8109043
170	404.00	2.6063814	1206.00	3.0813473	6.71	0.8267225
180	368.00	2.5658478	1495.00	3.1746412	7.00	0.8450980
190	347.00	2.5403295	1775.00	3.2491903	7.37	0.8674675
200	330.00	2.5185139	2092.00	3.3205617	7.79	0.8915375
210	320.00	2.5051500	2421.00	3.3839948	8.33	0.9206450
220	317.00	2.5010593	2769.00	3.4423229	9.09	0.9585639
230	313.00	2.4955443	3176.00	3.5018805	9.86	0.9938769
240	309.00	2.4899585	3557.00	3.5510839	10.51	1.0216027
250	304.00	2.4828736	3976.00	3.5994464	11.17	1.0480532
260	298.00	2.4742163	4452.00	3.6485552	11.80	1.0718820
270	290.00	2.4623980	4964.00	3.6958318	12.37	1.0923697
280	284.00	2.4533183	5458.00	3.7370335	12.87	1.1095785
290	278.00	2.4440448	5959.00	3.7751734	13.38	1.1264561
300	270.00	2.4313638	6461.00	3.8102997	13.65	1.1351327
310	263.00	2.4199557	6972.00	3.8433574	13.98	1.1455072
320	256.00	2.4082400	7491.00	3.8745398	14.23	1.1532049
330	250.00	2.3979400	8080.00	3.9074114	14.65	1.1658376
340	245.00	2.3891661	8650.00	3.9370161	14.98	1.1755118
350	239.00	2.3783979	9248.00	3.9660470	15.29	1.1844075
360	235.00	2.3710679	9848.00	3.9933480	15.65	1.1945143
370	232.00	2.3654880	10450.00	4.0191163	16.04	1.2052044
380	228.00	2.3579348	11031.00	4.0426149	16.35	1.2135178
390	224.00	2.3502480	11626.00	4.0654303	16.66	1.2216750
400	221.00	2.3443923	12227.00	4.0873199	16.97	1.2296818
410	218.00	2.3384565	12838.00	4.1084974	17.27	1.2372923
420	216.00	2.3344537	13349.00	4.1254487	17.56	1.2445245
430	214.00	2.3304138	13849.00	4.1414184	17.81	1.2506639
440	211.00	2.3242824	14337.00	4.1564583	18.01	1.2555137
450	209.00	2.3201463	14866.00	4.1721941	18.22	1.2605484
460	206.00	2.3138672	15454.00	4.1890469	18.41	1.2650538
470	203.00	2.3074960	16048.00	4.2054209	18.58	1.2690457
480	200.00	2.3010300	16654.00	4.2215186	18.78	1.2736956
490	198.00	2.2966652	17172.00	4.2348280	18.94	1.2773800

PEARSON CORRELATION COEFFICIENTS MATRIX

	Y	X1	X2
Y	1.0000000	-0.9955710	-0.9841432
X1	-0.9955710	1.0000000	0.9964640
X2	-0.9841432	0.9964640	1.0000000

```
******************************************************************
          RESULTS OF THE STANDARD LEARNING CURVE MODEL
******************************************************************
```

CASE	OBSERVED	PREDICTED	RESIDUAL	% DEVIATION
1	1088.00	1036.45	51.55	4.74
2	803.00	727.41	75.59	9.41
3	641.00	617.19	23.81	3.71
4	560.00	555.61	4.39	0.78
5	493.00	507.39	-14.39	-2.92
6	462.00	474.25	-12.25	-2.65
7	437.00	443.85	-6.85	-1.57
8	404.00	421.56	-17.56	-4.35
9	368.00	396.72	-28.72	-7.81
10	347.00	377.93	-30.93	-8.91
11	330.00	360.78	-30.78	-9.33
12	320.00	346.19	-26.19	-8.19
13	317.00	333.30	-16.30	-5.14
14	313.00	320.63	-7.63	-2.44
15	309.00	310.52	-1.52	-0.49
16	304.00	300.90	3.10	1.02
17	298.00	291.44	6.56	2.20
18	290.00	282.61	7.39	2.55
19	284.00	275.13	8.87	3.12
20	278.00	268.39	9.61	3.46
21	270.00	262.32	7.68	2.84
22	263.00	256.74	6.26	2.38
23	256.00	251.58	4.42	1.73
24	250.00	246.26	3.74	1.50
25	245.00	241.56	3.44	1.40
26	239.00	237.04	1.96	0.82
27	235.00	232.86	2.14	0.91
28	232.00	228.99	3.01	1.30
29	228.00	225.52	2.48	1.09
30	224.00	222.19	1.81	0.81
31	221.00	219.05	1.95	0.88
32	218.00	216.05	1.95	0.89
33	216.00	213.68	2.32	1.07
34	214.00	211.47	2.53	1.18
35	211.00	209.41	1.59	0.75
36	209.00	207.28	1.72	0.82
37	206.00	205.02	0.98	0.48
38	203.00	202.85	0.15	0.08
39	200.00	200.73	-0.73	-0.37
40	198.00	199.00	-1.00	-0.51

```
******************************************************************
THE EQUATION FOR THIS MODEL IS:      YHAT = B0 * X1 ** B1
IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B1 * LOG(X1)
WHERE: LOG(B0) = 3.49572    STD ERROR = 0.13455    B0 = 3131.24884
            B1 =-0.28262    STD ERROR = 0.00433
SUMMARY STATISTICS:
R SQUARED LOG   =0.99115          STD ERROR EST =    0.0164
MSE             =  0.00027        MSR           =  1.14390
F RATIO         =4255.4005        D. F. (N/D)   = 1/ 38
R SQUARED ACTUAL=0.98881        LEARNING FACTOR = 82.20945 PERCENT
DURBIN-WATSON STATISTIC= 0.327753
******************************************************************
```

RESULTS OF REGRESSION ON PRODUCTION RATE VARIABLE ALONE

CASE	OBSERVED	PREDICTED	RESIDUAL	% DEVIATION
1	1088.00	974.84	113.16	10.40
2	803.00	658.04	144.96	18.05
3	641.00	590.83	50.17	7.83
4	560.00	546.65	13.35	2.38
5	493.00	516.61	-23.61	4.79
6	462.00	482.04	-20.04	-4.34
7	437.00	447.24	-10.24	-2.34
8	404.00	435.28	-31.28	-7.74
9	368.00	421.80	-53.80	-14.62
10	347.00	405.94	-58.94	-16.99
11	330.00	389.54	-59.54	-18.04
12	320.00	370.60	-50.60	-15.81
13	317.00	347.29	-30.29	-9.56
14	313.00	326.90	-13.90	-4.44
15	309.00	311.74	-2.74	-0.89
16	304.00	297.93	6.07	2.00
17	298.00	286.02	11.98	4.02
18	290.00	276.15	13.85	4.77
19	284.00	268.13	15.87	5.59
20	278.00	260.49	17.51	6.30
21	270.00	256.65	13.35	4.95
22	263.00	252.13	10.87	4.13
23	256.00	248.82	7.18	2.80
24	250.00	243.50	6.50	2.60
25	245.00	239.50	5.50	2.25
26	239.00	235.87	3.13	1.31
27	235.00	231.83	3.17	1.35
28	232.00	227.62	4.38	1.89
29	228.00	224.40	3.60	1.58
30	224.00	221.29	2.71	1.21
31	221.00	218.27	2.73	1.23
32	218.00	215.45	2.55	1.17
33	216.00	212.79	3.21	1.48
34	214.00	210.57	3.43	1.60
35	211.00	208.83	2.17	1.03
36	209.00	207.03	1.97	0.94
37	206.00	205.44	0.56	0.27
38	203.00	204.04	-1.04	-0.51
39	200.00	202.42	-2.42	-1.21
40	198.00	201.15	-3.15	-1.59

```
THE EQUATION FOR THIS MODEL IS: "     YHAT = B0 * X2 ** B2
IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B2 * LOG(X2)
WHERE: LOG(B0) = 3.25379    STD ERROR = 0.23957    B0 = 1793.86990
            B2 =-0.74392    STD ERROR = 0.02175
SUMMARY STATISTICS:
R SQUARED LOG   =0.96854          STD ERROR EST =     0.0309
MSE             =  0.00096        MSR           =  1.11700
F RATIO         =1169.7950        D. F. (N/D)   = 1/ 38
R SQUARED ACTUAL=0.95679
DURBIN-WATSON STATISTIC= 0.277205
```

****

RESULTS OF COMBINED CUMULATIVE PRODUCTION AND PRODUCTION RATE MODEL

****

CASE	OBSERVED	PREDICTED	RESIDUAL	% DEVIATION
1	1088.00	1088.13	-0.13	-0.01
2	883.00	883.15	-0.15	-0.02
3	641.00	640.73	0.27	0.04
4	560.00	560.09	-0.09	-0.02
5	493.00	492.67	0.33	0.07
6	462.00	461.92	0.08	0.02
7	437.00	437.10	-0.10	-0.02
8	404.00	404.12	-0.12	-0.03
9	368.00	368.24	-0.24	-0.07
10	347.00	347.04	-0.04	-0.01
11	330.00	329.59	0.41	0.12
12	320.00	319.59	0.41	0.13
13	317.00	317.50	-0.50	-0.16
14	313.00	313.28	-0.28	-0.09
15	309.00	308.97	0.03	0.01
16	304.00	304.32	-0.32	-0.10
17	298.00	297.89	0.11	0.04
18	290.00	290.45	-0.45	-0.15
19	284.00	283.75	0.25	0.09
20	278.00	278.21	-0.21	-0.07
21	270.00	269.56	0.44	0.16
22	263.00	262.80	0.20	0.08
23	256.00	255.53	0.47	0.18
24	250.00	250.29	-0.29	-0.11
25	245.00	244.84	0.16	0.07
26	239.00	239.34	-0.34	-0.14
27	235.00	235.07	-0.07	-0.03
28	232.00	231.63	0.37	0.16
29	228.00	227.91	0.09	0.04
30	224.00	224.38	-0.38	-0.17
31	221.00	221.13	-0.13	-0.06
32	218.00	217.97	0.03	0.02
33	216.00	215.95	0.05	0.02
34	214.00	213.78	0.22	0.10
35	211.00	211.38	-0.38	-0.18
36	209.00	208.88	0.12	0.06
37	206.00	205.88	0.12	0.06
38	203.00	202.85	0.15	0.07
39	200.00	200.20	-0.20	-0.10
40	198.00	197.97	0.03	0.01

****

THE EQUATION FOR THIS MODEL IS: YHAT = B0 * X1 ** B1 * X2 **B2

IN LOG FORM THIS MODEL BECOMES: LOG(YHAT) = LOG(B0) + B1 * LOG(X1) + B2 * LOG(X2)

WHERE: LOG(B0) = 3.75380 STD ERROR = 0.00116 B0 = 5672.84668

B1 =-0.59957 STD ERROR = 0.00134 F* =00532.2109

B2 = 0.84696 STD ERROR = 0.00356 F* =56384.9604

SUMMARY STATISTICS:

R SQUARED LOG =0.99999 STD ERROR EST = 0.0004

MSE = 0.00000 MSR = 0.57705

F RATIO =7988.2812 D. F. (N/D) = 2/ 37

R SQUARED ACTUAL=1.00000

DURBIN-WATSON STATISTIC= 2.300320

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SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 40 WHICH HAS AN OBSERVED VALUE OF: 198.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
39	199.06	-0.53	3129.01	-0.28252	197.97	0.02	5673.27	-0.59961	0.84704
38	199.10	-0.56	3127.20	-0.28244	197.98	0.01	5671.21	-0.59947	0.84673
37	199.10	-0.56	3127.32	-0.28244	197.97	0.01	5671.58	-0.59947	0.84669
36	199.05	-0.53	3129.39	-0.28254	197.97	0.02	5671.34	-0.59941	0.84649
35	198.94	-0.47	3133.42	-0.28273	197.96	0.02	5671.37	-0.59938	0.84637
34	198.83	-0.42	3137.51	-0.28292	197.98	0.01	5671.01	-0.59945	0.84669
33	198.64	-0.32	3144.39	-0.28324	197.97	0.02	5671.22	-0.59941	0.84650
32	198.45	-0.22	3151.43	-0.28357	197.96	0.02	5671.03	-0.59937	0.84639
31	198.25	-0.13	3158.24	-0.28389	197.96	0.02	5671.17	-0.59937	0.84637
30	198.04	-0.02	3165.76	-0.28424	197.97	0.02	5670.86	-0.59938	0.84643
29	197.81	0.09	3173.66	-0.28462	198.00	-0.00	5669.98	-0.59943	0.84671
28	197.50	0.25	3184.44	-0.28513	198.00	0.00	5670.05	-0.59941	0.84664

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 39 WHICH HAS AN OBSERVED VALUE OF: 200.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
38	200.83	-0.42	3127.20	-0.28244	200.21	-0.10	5671.21	-0.59947	0.84673
37	200.83	-0.42	3127.32	-0.28244	200.20	-0.10	5671.58	-0.59947	0.84669
36	200.78	-0.39	3129.39	-0.28254	200.19	-0.10	5671.34	-0.59941	0.84649
35	200.67	-0.33	3133.42	-0.28273	200.18	-0.09	5671.37	-0.59938	0.84637
34	200.56	-0.28	3137.51	-0.28292	200.21	-0.10	5671.01	-0.59945	0.84669
33	200.37	-0.19	3144.39	-0.28324	200.19	-0.10	5671.22	-0.59941	0.84650
32	200.18	-0.09	3151.43	-0.28357	200.19	-0.09	5671.03	-0.59937	0.84639
31	199.99	0.01	3158.24	-0.28389	200.19	-0.09	5671.17	-0.59937	0.84637
30	199.77	0.11	3165.76	-0.28424	200.20	-0.10	5670.86	-0.59938	0.84643
29	199.55	0.23	3173.66	-0.28462	200.23	-0.11	5669.98	-0.59943	0.84671
28	199.23	0.38	3184.44	-0.28513	200.22	-0.11	5670.05	-0.59941	0.84664
27	198.83	0.59	3198.10	-0.28578	200.19	-0.09	5670.15	-0.59930	0.84619

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 38 WHICH HAS AN OBSERVED VALUE OF: 203.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
37	202.94	0.03	3127.32	-0.28244	202.85	0.07	5671.58	-0.59947	0.84669
36	202.89	0.05	3129.39	-0.28254	202.84	0.08	5671.34	-0.59941	0.84649
35	202.78	0.11	3133.42	-0.28273	202.83	0.08	5671.37	-0.59938	0.84637
34	202.67	0.16	3137.51	-0.28292	202.86	0.07	5671.01	-0.59945	0.84669
33	202.49	0.25	3144.39	-0.28324	202.84	0.08	5671.22	-0.59941	0.84650
32	202.29	0.35	3151.43	-0.28357	202.84	0.08	5671.03	-0.59937	0.84639
31	202.10	0.44	3158.24	-0.28389	202.84	0.08	5671.17	-0.59937	0.84637
30	201.89	0.55	3165.76	-0.28424	202.85	0.08	5670.86	-0.59938	0.84643
29	201.66	0.66	3173.66	-0.28462	202.88	0.06	5669.98	-0.59943	0.84671
28	201.35	0.81	3184.44	-0.28513	202.87	0.06	5670.05	-0.59941	0.84664
27	200.94	1.01	3198.10	-0.28578	202.84	0.08	5670.15	-0.59938	0.84619
26	200.57	1.20	3210.66	-0.28638	202.85	0.08	5669.98	-0.59938	0.84623

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 37 WHICH HAS AN OBSERVED VALUE OF: 206.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
36	205.06	0.45	3129.39	-0.28254	205.87	0.06	5671.34	-0.59941	0.84649
35	204.96	0.51	3133.42	-0.28273	205.86	0.07	5671.37	-0.59938	0.84637
34	204.85	0.56	3137.51	-0.28292	205.89	0.05	5671.01	-0.59945	0.84669
33	204.66	0.65	3144.39	-0.28324	205.87	0.06	5671.22	-0.59941	0.84650
32	204.47	0.74	3151.43	-0.28357	205.87	0.06	5671.03	-0.59937	0.84639
31	204.28	0.84	3158.24	-0.28389	205.87	0.06	5671.17	-0.59937	0.84637
30	204.07	0.94	3165.76	-0.28424	205.88	0.06	5670.86	-0.59938	0.84643
29	203.84	1.05	3173.66	-0.28462	205.91	0.04	5669.98	-0.59943	0.84671
28	203.53	1.20	3184.44	-0.28513	205.90	0.05	5670.05	-0.59941	0.84664
27	203.12	1.40	3198.10	-0.28578	205.87	0.06	5670.15	-0.59938	0.84619
26	202.75	1.58	3210.66	-0.28638	205.88	0.06	5669.98	-0.59938	0.84623
25	202.33	1.78	3224.20	-0.28702	205.91	0.04	5669.57	-0.59940	0.84663

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 36 WHICH HAS AN OBSERVED VALUE OF: 209.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
35	207.22	0.85	3133.42	-0.28273	208.86	0.06	5671.37	-0.59938	0.84637
34	207.11	0.91	3137.51	-0.28292	208.89	0.05	5671.01	-0.59945	0.84669
33	206.92	0.99	3144.39	-0.28324	208.87	0.06	5671.22	-0.59941	0.84650
32	206.73	1.09	3151.43	-0.28357	208.87	0.06	5671.03	-0.59937	0.84639
31	206.54	1.18	3158.24	-0.28389	208.87	0.06	5671.17	-0.59937	0.84637
30	206.33	1.28	3165.76	-0.28424	208.88	0.06	5670.86	-0.59938	0.84643
29	206.10	1.39	3173.66	-0.28462	208.91	0.04	5669.98	-0.59943	0.84671
28	205.79	1.54	3184.44	-0.28513	208.90	0.05	5670.05	-0.59941	0.84664
27	205.39	1.73	3198.10	-0.28578	208.87	0.06	5670.15	-0.59930	0.84619
26	205.01	1.91	3210.66	-0.28638	208.88	0.06	5669.98	-0.59930	0.84623
25	204.60	2.11	3224.20	-0.28702	208.91	0.04	5669.57	-0.59940	0.84663
24	203.90	2.40	3244.40	-0.28799	208.90	0.05	5669.29	-0.59932	0.84635

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 35 WHICH HAS AN OBSERVED VALUE OF: 211.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
34	209.24	0.83	3137.51	-0.28292	211.39	-0.19	5671.01	-0.59945	0.84669
33	209.06	0.92	3144.39	-0.28324	211.38	-0.18	5671.22	-0.59941	0.84650
32	208.86	1.01	3151.43	-0.28357	211.37	-0.18	5671.03	-0.59937	0.84639
31	208.67	1.10	3158.24	-0.28389	211.37	-0.17	5671.17	-0.59937	0.84637
30	208.46	1.20	3165.76	-0.28424	211.38	-0.18	5670.86	-0.59938	0.84643
29	208.24	1.31	3173.66	-0.28462	211.41	-0.19	5669.98	-0.59943	0.84671
28	207.93	1.46	3184.44	-0.28513	211.40	-0.19	5670.05	-0.59941	0.84664
27	207.52	1.65	3198.10	-0.28578	211.37	-0.18	5670.15	-0.59930	0.84619
26	207.15	1.82	3210.66	-0.28638	211.38	-0.18	5669.98	-0.59930	0.84623
25	206.74	2.02	3224.20	-0.28702	211.41	-0.20	5669.57	-0.59940	0.84663
24	206.12	2.31	3244.40	-0.28799	211.40	-0.19	5669.29	-0.59932	0.84635
23	205.37	2.67	3260.45	-0.28914	211.43	-0.21	5669.51	-0.59947	0.84690

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 34 WHICH HAS AN OBSERVED VALUE OF: 214.00

# CASES	REDUCED (LEARNING CURVE) MODEL				FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL				
USED	PREDICTION	% DEVIATION	EST B0	EST B1	PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
33	211.12	1.35	3144.39	-0.28324	213.78	0.10	5671.22	-0.59941	0.84650
32	210.92	1.44	3151.43	-0.28357	213.78	0.11	5671.03	-0.59937	0.84639
31	210.74	1.53	3158.24	-0.28389	213.77	0.11	5671.17	-0.59937	0.84637
30	210.53	1.62	3165.76	-0.28424	213.78	0.10	5670.86	-0.59938	0.84643
29	210.30	1.73	3173.66	-0.28462	213.81	0.09	5669.98	-0.59943	0.84671
28	209.99	1.87	3184.44	-0.28513	213.81	0.09	5670.05	-0.59941	0.84664
27	209.59	2.06	3198.10	-0.28578	213.77	0.11	5670.15	-0.59938	0.84619
26	209.21	2.24	3210.66	-0.28638	213.78	0.10	5669.98	-0.59938	0.84623
25	208.80	2.43	3224.20	-0.28702	213.82	0.09	5669.57	-0.59940	0.84663
24	208.18	2.72	3244.40	-0.28799	213.80	0.09	5669.29	-0.59932	0.84635
23	207.43	3.07	3268.45	-0.28914	213.84	0.08	5669.51	-0.59947	0.84690
22	206.49	3.51	3298.29	-0.29058	213.78	0.10	5668.70	-0.59920	0.84597

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 33 WHICH HAS AN OBSERVED VALUE OF: 216.00

# CASES	REDUCED (LEARNING CURVE) MODEL				FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL				
USED	PREDICTION	% DEVIATION	EST B0	EST B1	PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
32	213.14	1.33	3151.43	-0.28357	215.94	0.03	5671.03	-0.59937	0.84639
31	212.95	1.41	3158.24	-0.28389	215.94	0.03	5671.17	-0.59937	0.84637
30	212.74	1.51	3165.76	-0.28424	215.95	0.03	5670.86	-0.59938	0.84643
29	212.51	1.61	3173.66	-0.28462	215.98	0.01	5669.98	-0.59943	0.84671
28	212.20	1.76	3184.44	-0.28513	215.97	0.01	5670.05	-0.59941	0.84664
27	211.80	1.94	3198.10	-0.28578	215.94	0.03	5670.15	-0.59938	0.84619
26	211.43	2.12	3210.66	-0.28638	215.94	0.03	5669.98	-0.59938	0.84623
25	211.02	2.31	3224.20	-0.28702	215.98	0.01	5669.57	-0.59940	0.84663
24	210.40	2.59	3244.40	-0.28799	215.96	0.02	5669.29	-0.59932	0.84635
23	209.65	2.94	3268.45	-0.28914	216.00	-0.00	5669.51	-0.59947	0.84690
22	208.71	3.38	3298.29	-0.29058	215.95	0.03	5668.70	-0.59920	0.84597
21	207.39	3.99	3339.76	-0.29256	215.91	0.04	5667.92	-0.59902	0.84537

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 32 WHICH HAS AN OBSERVED VALUE OF: 218.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
31	215.32	1.23	3158.24	-0.28389	217.95	0.02	5671.17	-0.59937	0.84637
30	215.11	1.33	3165.76	-0.28424	217.96	0.02	5670.86	-0.59938	0.84643
29	214.89	1.43	3173.66	-0.28462	218.00	0.00	5669.98	-0.59943	0.84671
28	214.58	1.57	3184.44	-0.28513	217.99	0.00	5670.05	-0.59941	0.84664
27	214.18	1.75	3198.10	-0.28578	217.96	0.02	5670.15	-0.59930	0.84619
26	213.81	1.92	3210.66	-0.28638	217.96	0.02	5669.98	-0.59930	0.84623
25	213.40	2.11	3224.20	-0.28702	218.00	0.00	5669.57	-0.59940	0.84663
24	212.78	2.40	3244.40	-0.28799	217.98	0.01	5669.29	-0.59932	0.84635
23	212.03	2.74	3268.45	-0.28914	218.02	-0.01	5669.51	-0.59947	0.84690
22	211.09	3.17	3298.29	-0.29058	217.96	0.02	5668.70	-0.59920	0.84597
21	209.77	3.78	3339.76	-0.29256	217.93	0.03	5667.92	-0.59902	0.84537
20	208.04	4.57	3393.89	-0.29513	217.84	0.07	5664.33	-0.59840	0.84339

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 31 WHICH HAS AN OBSERVED VALUE OF: 221.00

# CASES USED	REDUCED (LEARNING CURVE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL: PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
30	218.11	1.31	3165.76	-0.28424	221.12	-0.06	5670.86	-0.59938	0.84643
29	217.89	1.41	3173.66	-0.28462	221.16	-0.07	5669.98	-0.59943	0.84671
28	217.58	1.55	3184.44	-0.28513	221.15	-0.07	5670.05	-0.59941	0.84664
27	217.18	1.73	3198.10	-0.28578	221.12	-0.05	5670.15	-0.59930	0.84619
26	216.81	1.90	3210.66	-0.28638	221.12	-0.06	5669.98	-0.59930	0.84623
25	216.40	2.08	3224.20	-0.28702	221.16	-0.07	5669.57	-0.59940	0.84663
24	215.79	2.36	3244.40	-0.28799	221.14	-0.06	5669.29	-0.59932	0.84635
23	215.04	2.70	3268.45	-0.28914	221.18	-0.08	5669.51	-0.59947	0.84690
22	214.10	3.12	3298.29	-0.29058	221.12	-0.06	5668.70	-0.59920	0.84597
21	212.78	3.72	3339.76	-0.29256	221.09	-0.04	5667.92	-0.59902	0.84537
20	211.06	4.50	3393.89	-0.29513	221.00	-0.00	5664.33	-0.59840	0.84339
19	208.76	5.54	3466.00	-0.29853	221.02	-0.01	5664.04	-0.59849	0.84366

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 30 WHICH HAS AN OBSERVED VALUE OF: 224.00

# CASES	REDUCED (LEARNING CURVE) MODEL				FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL				
USED	PREDICTION	% DEVIATION	EST B0	EST B1	PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
29	221.04	1.32	3173.66	-0.28462	224.41	-0.18	5669.98	-0.59943	0.84671
28	220.73	1.46	3184.44	-0.28513	224.40	-0.18	5670.05	-0.59941	0.84664
27	220.33	1.64	3198.10	-0.28578	224.37	-0.17	5670.15	-0.59930	0.84619
26	219.96	1.80	3210.66	-0.28638	224.38	-0.17	5669.98	-0.59930	0.84623
25	219.56	1.98	3224.20	-0.28702	224.41	-0.18	5669.57	-0.59940	0.84663
24	218.94	2.26	3244.40	-0.28799	224.40	-0.18	5669.29	-0.59932	0.84635
23	218.20	2.59	3268.45	-0.28914	224.43	-0.19	5669.51	-0.59947	0.84690
22	217.26	3.01	3298.29	-0.29058	224.38	-0.17	5668.70	-0.59920	0.84597
21	215.94	3.60	3339.76	-0.29256	224.34	-0.15	5667.92	-0.59902	0.84537
20	214.22	4.37	3393.89	-0.29513	224.26	-0.12	5664.33	-0.59840	0.84339
19	211.92	5.39	3466.00	-0.29853	224.27	-0.12	5664.84	-0.59849	0.84366
18	209.29	6.57	3549.33	-0.30240	224.17	-0.08	5660.02	-0.59772	0.84127

SHORTRANGE PREDICTIVE ABILITY COMPARISON

THE DATA PRESENTED BELOW IS FOR CASE # 29 WHICH HAS AN OBSERVED VALUE OF: 228.00

# CASES	REDUCED (LEARNING CURVE) MODEL				FULL (CUMULATIVE PRODUCTION & PRODUCTION RATE) MODEL				
USED	PREDICTION	% DEVIATION	EST B0	EST B1	PREDICTION	% DEVIATION	EST B0	EST B1	EST B2
28	224.06	1.73	3184.44	-0.28513	227.93	0.03	5670.05	-0.59941	0.84664
27	223.67	1.90	3198.10	-0.28578	227.90	0.05	5670.15	-0.59930	0.84619
26	223.30	2.06	3210.66	-0.28638	227.90	0.04	5669.98	-0.59930	0.84623
25	222.89	2.24	3224.20	-0.28702	227.94	0.03	5669.57	-0.59940	0.84663
24	222.28	2.51	3244.40	-0.28799	227.92	0.03	5669.29	-0.59932	0.84635
23	221.54	2.84	3268.45	-0.28914	227.96	0.02	5669.51	-0.59947	0.84690
22	220.60	3.25	3298.29	-0.29058	227.90	0.04	5668.70	-0.59920	0.84597
21	219.29	3.82	3339.76	-0.29256	227.87	0.06	5667.92	-0.59902	0.84537
20	217.57	4.58	3393.09	-0.29513	227.78	0.10	5664.33	-0.59840	0.84339
19	215.27	5.58	3466.00	-0.29853	227.79	0.09	5664.84	-0.59849	0.84366
18	212.64	6.74	3549.33	-0.30240	227.69	0.13	5660.02	-0.59772	0.84127
17	209.70	8.03	3642.99	-0.30670	227.76	0.10	5663.39	-0.59825	0.84293

SUMMARY OF PREDICTIVE ABILITY TESTS RESULTS

ITEMS OF INTEREST	REDUCED MODEL	FULL MODEL
AVERAGE ABSOLUTE DEVIATION	3.84	0.16
VARIANCE OF ABSOLUTE DEVIATIONS	10.60	0.01
TEST STATISTIC (SEE NOTE)	---	13.58
TOTAL NUMBER OF TEST SITUATIONS	144	144
NUMBER OF PREDICTIONS WITHIN 5%	138	144
PERCENT OF PREDICTIONS WITHIN 5%	95.	100.
NUMBER OF PREDICTIONS WITHIN 10%	144	144
PERCENT OF PREDICTIONS WITHIN 10%	100.	100.

NOTE: IN TESTING FOR STATISTICAL SIGNIFICANCE USE STUDENT'S T DISTRIBUTION IF THE NUMBER OF TEST SITUATIONS ARE LESS THAN 60; OTHERWISE USE STANDARD NORMAL DISTRIBUTION. IN EITHER CASE THIS IS A ONE TAILED TEST. IF THE TEST STATISTIC IS GREATER THAN THE CRITICAL STATISTIC ONE MAY CONCLUDE THAT THE AVERAGE ABSOLUTE DEVIATION OBTAINED WITH THE FULL MODEL IS SIGNIFICANTLY LESS THAN THAT OBTAINED WITH THE REDUCED MODEL.
FILES LOGFILE,STDLEARN,REDHOURS,AND FULLMODL WRITTEN.

PROJECTION AND SENSITIVITY MATRIX

PROJECTED CUMULATIVE UNITS	PROJECTED PRODUCTION RATES								
	13.26	15.15	17.05	18.94	20.83	22.73	24.62	26.52	28.41
25929	114.3	128.0	141.4	154.6	167.6	180.5	193.1	205.6	218.0
26101	113.9	127.5	140.9	154.0	167.0	179.7	192.3	204.8	217.1
26273	113.4	127.0	140.3	153.4	166.3	179.0	191.6	204.0	216.3
26444	113.0	126.5	139.8	152.8	165.7	178.3	190.8	203.2	215.4
26616	112.5	126.0	139.2	152.2	165.0	177.6	190.1	202.4	214.6
26788	112.1	125.5	138.7	151.6	164.4	177.0	189.4	201.6	213.8
26960	111.7	125.0	138.2	151.1	163.8	176.3	188.6	200.9	213.0
27131	111.3	124.6	137.6	150.5	163.1	175.6	187.9	200.1	212.[illegible]
27303	110.8	124.1	137.1	149.9	162.5	175.0	187.2	199.4	211.3
27475	110.4	123.6	136.6	149.4	161.9	174.3	186.5	198.6	210.6
27646	110.0	123.2	136.1	148.8	161.3	173.6	185.8	197.9	209.8
27818	109.6	122.7	135.6	148.2	160.7	173.0	185.1	197.1	209.0
27990	109.2	122.3	135.1	147.7	160.1	172.4	184.5	196.4	208.2
28162	108.8	121.8	134.6	147.2	159.5	171.7	183.8	195.7	207.5
28333	108.4	121.4	134.1	146.6	159.0	171.1	183.1	195.0	206.[illegible]
28505	108.0	120.9	133.6	146.1	158.4	170.5	182.4	194.3	206.0
28677	107.6	120.5	133.1	145.6	157.8	169.9	181.8	193.6	205.2
28848	107.2	120.1	132.7	145.1	157.2	169.3	181.1	192.9	204.5
29020	106.9	119.6	132.2	144.5	156.7	168.7	180.5	192.2	203.8
29192	106.5	119.2	131.7	144.0	156.1	168.1	179.9	191.5	203.0
29364	106.1	118.8	131.3	143.5	155.6	167.5	179.2	190.8	202.3
29535	105.7	118.4	130.8	143.0	155.0	166.9	178.6	190.2	201.6
29707	105.4	118.0	130.4	142.5	154.5	166.3	178.0	189.5	200.9
29879	105.0	117.6	129.9	142.0	154.0	165.7	177.4	188.9	200.2
30050	104.6	117.2	129.5	141.5	153.4	165.2	176.8	188.2	199.5
30222	104.3	116.8	129.0	141.1	152.9	164.6	176.2	187.6	198.9
30394	103.9	116.4	128.6	140.6	152.4	164.1	175.6	186.9	198.2
30566	103.6	116.0	128.1	140.1	151.9	163.5	175.0	186.3	197.5
30737	103.2	115.6	127.7	139.6	151.4	163.0	174.4	185.7	196.9
30909	102.9	115.2	127.3	139.2	150.9	162.4	173.8	185.1	196.2
31081	102.5	114.8	126.9	138.7	150.4	161.9	173.2	184.4	195.5
31253	102.2	114.4	126.4	138.3	149.9	161.3	172.7	183.8	194.9
31424	101.9	114.1	126.0	137.8	149.4	160.8	172.1	183.2	194.3
31596	101.5	113.7	125.6	137.3	148.9	160.3	171.5	182.6	193.6
31768	101.2	113.3	125.2	136.9	148.4	159.8	171.0	182.0	193.0
31939	100.9	113.0	124.8	136.5	147.9	159.3	170.4	181.5	192.4
32111	100.6	112.6	124.4	136.0	147.5	158.7	169.9	180.9	191.8
32283	100.2	112.2	124.0	135.6	147.0	158.2	169.3	180.3	191.1
32455	99.9	111.9	123.6	135.2	146.5	157.7	168.8	179.7	190.5
32626	99.6	111.5	123.2	134.7	146.1	157.2	168.3	179.2	189.9
32798	99.3	111.2	122.8	134.3	145.6	156.7	167.7	178.6	189.3
32970	99.0	110.8	122.5	133.9	145.1	156.2	167.2	178.0	188.7
33141	98.7	110.5	122.1	133.5	144.7	155.8	166.7	177.5	188.2
33313	98.4	110.1	121.7	133.1	144.2	155.3	166.2	176.9	187.6
33485	98.1	109.8	121.3	132.7	143.8	154.8	165.7	176.4	187.0
33657	97.8	109.5	121.0	132.2	143.4	154.3	165.2	175.8	186.4
33828	97.5	109.1	120.6	131.8	142.9	153.9	164.6	175.3	185.9
34000	97.2	108.8	120.2	131.4	142.5	153.4	164.1	174.8	185.3
34172	96.9	108.5	119.9	131.0	142.1	152.9	163.7	174.3	184.7
34343	96.6	108.2	119.5	130.7	141.6	152.5	163.2	173.7	184.2

NOTE: 1. PROJECTED VALUES FOR DIRECT LABOR HOURS MAY BE READ FROM THE ABOVE MATRIX BY MATCHING A GIVEN PRODUCTION RATE WITH A GIVEN NUMBER OF CUMULATIVE UNITS AND READING THE VALUE FOR DIRECT LABOR HOURS FOUND AT THE INTERSECTION OF THE CORRESPONDING ROW AND COLUMN. FORECASTING MODEL IS THE CUMULATIVE PRODUCTION & PRODUCTION RATE MODEL.

2. PROJECTION INTERVAL FOR CUMULATIVE UNITS IS 1% OF THE LAST OBSERVED VALUE OF CUMULATIVE UNITS.

3. PROJECTION VALUES FOR PRODUCTION RATE ARE 70, 80, 90, 100, 110, 120, 130, 140, AND 150 PERCENT OF THE LAST OBSERVED VALUE OF PRODUCTION RATE.

PROJECTION AND SENSITIVITY MATRIX

PROJECTED CUMULATIVE UNITS	PROJECTED PRODUCTION RATES								
	13.26	15.15	17.05	18.94	20.83	22.73	24.62	26.52	28.41
17343	145.5	162.9	180.0	196.8	213.3	229.7	245.8	261.7	277.4
17515	144.6	161.9	178.9	195.6	212.1	228.3	244.3	260.1	275.8
17687	143.8	161.0	177.9	194.5	210.8	227.0	242.9	258.6	274.2
17858	143.0	160.1	176.9	193.4	209.6	225.7	241.5	257.1	272.6
18030	142.1	159.2	175.9	192.3	208.4	224.4	240.1	255.7	271.0
18202	141.3	158.3	174.9	191.2	207.2	223.1	238.7	254.2	269.5
18374	140.5	157.4	173.9	190.1	206.1	221.8	237.4	252.8	268.0
18545	139.8	156.5	172.9	189.0	204.9	220.6	236.1	251.4	266.5
18717	139.0	155.6	172.0	188.0	203.8	219.4	234.8	250.0	265.0
18889	138.2	154.8	171.0	187.0	202.7	218.2	233.5	248.6	263.6
19060	137.5	153.9	170.1	186.0	201.6	217.0	232.2	247.3	262.2
19232	136.7	153.1	169.2	185.0	200.5	215.9	231.0	246.0	260.8
19404	136.0	152.3	168.3	184.0	199.5	214.7	229.8	244.7	259.4
19576	135.3	151.5	167.4	183.0	198.4	213.6	228.6	243.4	258.0
19747	134.6	150.7	166.5	182.1	197.4	212.5	227.4	242.1	256.7
19919	133.9	149.9	165.7	181.1	196.3	211.4	226.2	240.8	255.3
20091	133.2	149.2	164.8	180.2	195.3	210.3	225.0	239.6	254.0
20262	132.5	148.4	164.0	179.3	194.3	209.2	223.9	238.4	252.7
20434	131.9	147.7	163.1	178.4	193.4	208.2	222.8	237.2	251.5
20606	131.2	146.9	162.3	177.5	192.4	207.1	221.6	236.0	250.2
20778	130.5	146.2	161.5	176.6	191.4	206.1	220.5	234.8	248.9
20949	129.9	145.5	160.7	175.7	190.5	205.1	219.5	233.7	247.7
21121	129.3	144.8	159.9	174.9	189.6	204.1	218.4	232.5	246.5
21293	128.6	144.0	159.2	174.0	188.6	203.1	217.3	231.4	245.3
21464	128.0	143.4	158.4	173.2	187.7	202.1	216.3	230.3	244.1
21636	127.4	142.7	157.6	172.4	186.8	201.1	215.2	229.2	243.0
21808	126.8	142.0	156.9	171.5	186.0	200.2	214.2	228.1	241.8
21980	126.2	141.3	156.2	170.7	185.1	199.2	213.2	227.0	240.7
22151	125.6	140.7	155.4	169.9	184.2	198.3	212.2	226.0	239.6
22323	125.1	140.0	154.7	169.2	183.4	197.4	211.2	224.9	238.5
22495	124.5	139.4	154.0	168.4	182.5	196.5	210.3	223.9	237.4
22667	123.9	138.7	153.3	167.6	181.7	195.6	209.3	222.9	236.3
22838	123.4	138.1	152.6	166.9	180.9	194.7	208.4	221.9	235.2
23010	122.8	137.5	151.9	166.1	180.1	193.8	207.4	220.9	234.2
23182	122.3	136.9	151.3	165.4	179.3	193.0	206.5	219.9	233.1
23353	121.7	136.3	150.6	164.6	178.5	192.1	205.6	218.9	232.1
23525	121.2	135.7	149.9	163.9	177.7	191.3	204.7	218.0	231.1
23697	120.7	135.1	149.3	163.2	176.9	190.5	203.8	217.0	230.1
23869	120.1	134.5	148.6	162.5	176.2	189.6	202.9	216.1	229.1
24040	119.6	133.9	148.0	161.8	175.4	188.8	202.1	215.2	228.1
24212	119.1	133.4	147.4	161.1	174.7	188.0	201.2	214.2	227.1
24384	118.6	132.8	146.7	160.4	173.9	187.2	200.4	213.3	226.2
24555	118.1	132.3	146.1	159.8	173.2	186.4	199.5	212.4	225.2
24727	117.6	131.7	145.5	159.1	172.5	185.7	198.7	211.6	224.3
24899	117.1	131.2	144.9	158.4	171.8	184.9	197.9	210.7	223.4
25071	116.6	130.6	144.3	157.8	171.0	184.1	197.0	209.8	222.4
25242	116.2	130.1	143.7	157.1	170.4	183.4	196.2	209.0	221.5
25414	115.7	129.6	143.1	156.5	169.7	182.6	195.4	208.1	220.6
25586	115.2	129.0	142.6	155.9	169.0	181.9	194.7	207.3	219.7
25757	114.8	128.5	142.0	155.3	168.3	181.2	193.9	206.4	218.9

NOTE: 1. PROJECTED VALUES FOR DIRECT LABOR HOURS MAY BE READ FROM THE ABOVE MATRIX BY MATCHING A GIVEN PRODUCTION RATE WITH A GIVEN NUMBER OF CUMULATIVE UNITS AND READING THE VALUE FOR DIRECT LABOR HOURS FOUND AT THE INTERSECTION OF THE CORESPONDING ROW AND COLUMN. FORECASTING MODEL IS THE CUMULATIVE PRODUCTION & PRODUCTION RATE MODEL.

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SELECTED BIBLIOGRAPHY

A. REFERENCES CITED

1. Alchian, Armen A., and William R. Allen. University Economics. Belmont CA: Wadsworth Publishing Company, Inc., 1964.

2. Asher, Harold. "Cost Quantity Relationships in the Airframe Industry." Unpublished research report No. R-291. The Rand Corporation, Santa Monica CA, 1956.

3. Clark, Donald S., and Thomas F. McNeill. Cost Estimating and Contract Pricing. New York: American Elsevier Publishing Company, Inc., 1966.

4. Cochran, E. B. Planning Production Costs: Using the Improvement Curve. San Francisco: Chandler Publishing Company, 1968.

5. Congleton, Captain Duane E., USAF, and Major David W. Kinton, USAF. "An Empirical Study of the Impact of a Production Rate Change on the Direct Labor Requirements for an Airframe Manufacturing Program." Unpublished master's thesis, LSSR 23-77B, AFIT/LSGR, Wright-Patterson AFB OH, 1977. AD-A052720.

6. Crozier, Captain Michael W., USAF, and Captain Edward J. J. McGann, Jr., USAF. "An Investigation of Changes in Direct Labor Requirements Resulting from Changes in Aircraft Engine Production Rate." Unpublished master's thesis, LSSR 22-79B, AFIT/LSGR, Wright-Patterson AFB OH, 1979. AD-A077649.

7. Ilderton, Robert Blair. "Methods of Fitting Learning Curves to Lot Data Based on Assumptions and Techniques of Regression Analysis." Unpublished master's thesis, George Washington University, Washington DC, 1970. AD-A011583.

8. Johnson, Gordon J. "The Analysis of Direct Labor Costs for Production Program Stretchouts," National Management Journal, Spring 1969, pp. 25-41.

9. Large, Joseph P., Karl Hoffmayer, and Frank Kontrovich. "Production Rate and Production Cost." Unpublished research report No. R-1609-PA&E, The Rand Corporation, Santa Monica CA, 1974.

10. Neter, John, and William Wasserman. Applied Linear Statistical Models. Homewood IL: Richard D. Irwin, Inc., 1974.

11. ________ and G.A. Whitmore. Applied Statistics. Boston: Allyn and Bacon, Inc., 1978.

12. Orsini, Captain Joseph A., USAF. "An Analysis of Theoretical and Empirical Advances in Learning Curve Concepts Since 1966." Unpublished master's thesis, GSA/SM/70-12, AFIT/SE, Wright-Patterson AFB OH, 1970. AD875892.

13. Ostwald, Phillip F. Cost Estimating for Engineering and Management. Engelwood Cliffs NJ: Prentice-Hall, 1974.

14. Shields, Major Matthew D. Principles of Contract Pricing. Extension Course Institute, Gunter AFS AL, 1979.

15. Smith, Lieutenant Colonel Larry L., USAF. "An Investigation of Changes in Direct Labor Requirements Resulting from Changes in Airframe Production Rate." Unpublished doctoral dissertation, Department of Marketing, Transportation and Business Environment, University of Oregon, Eugene OR, 1976. AD-0926112.

16. Stevens, Captain David Y., and Captain Jimmie Thomerson, USAF. "An Investigation of Changes in Direct Labor Requirements Resulting from Changes in Avionics Production Rate." Unpublished master's thesis, LSSR 11-79A, AFIT/LSGR, Wright-Patterson AFB OH, 1979. AD-A077725.

17. U.S. Department of Defense. Armed Services Procurement Regulation Manual. ASPM No. 1. Washington: Government Printing Office, September 1975.

18. Wonnacott, Thomas H., and Ronald J. Wonnacott. Introductory Statistics for Business and Economics. 2d ed. New York: John Wiley & Sons, 1977.

B. RELATED SOURCES

Brewer, Glenn M. "The Learning Curve in the Airframe Industry." Unpublished master's thesis, SLSR-18-65, AFIT/SL, Wright-Patterson AFB OH, 1965.

Brockman, Major William F., USAF, and Major Freddie D. Dickens, USAF. "Investigation of Learning Curve and Cost Estimation Methods for Cargo Aircraft." Unpublished research paper, SGM/SM/67-2/7, AFIT/SE, Wright-Patterson AFB OH, 1967. AD665464.

Hale, Jack R. "Learning Curve: Analyzing Major Program Changes." Working paper, AFIT/LSG, Department of Special Management Techniques, Wright-Patterson AFB OH, 1973.

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